Skewness and Monetary Policy Decisions*

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Francesco Fusari†

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Abstract

This paper studies the relationship between monetary policy decisions taken by the Federal Open Market Committee (FOMC) and higher moments of expected economic outcomes. First, I employ quantile factor models to characterize the conditional distribution of central bank economic projections and construct indicators of uncertainty and skewness. Second, I find that the skewness of expected output growth and inflation rate is a crucial predictor of the changes in the intended federal funds rate deliberated by the FOMC. This empirical evidence is found to be reconcilable with central bank's optimal behavior under non-linear weighting of probability. My findings suggest that considering central moments only is not enough to fully capture the systematic component of monetary policy and lead therefore to important implications for the identification of monetary policy shocks. Specifically, I find that conditioning on higher moments allows to identify monetary policy shocks exhibiting lower predictability and that generate theoretically consistent effects on the economy.

Keywords: Monetary policy shocks, Quantile regressions, Factor models.

JEL Codes: E52; C51

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†University of Surrey, UK. Address: Elizabeth Fry Building (AD), University of Surrey; Guildford GU2 7XH. Email: f.fusari@surrey.ac.uk.

1 Introduction

"A central bank needs to consider not only the most likely future path for the economy, but also the distribution of possible outcomes about that path."

Fed Chairman Alan Greenspan (Meetings of the American Economic Association, January 2004)

"Most FOMC participants agreed that risks to inflation were skewed to the upside and judged that uncertainty about economic growth over the next couple of years was elevated."

Minutes of the FOMC Meeting, June 2022

Central banks makes choices in an uncertain environment, where beliefs about future economic conditions play an essential role. In the United States, specifically, the policy actions taken by the Federal Open Market Committee (FOMC) are informed by the Greenbook. This document is prepared by the staff of the Federal Reserve Board before each FOMC meeting and contains point forecasts for several macroeconomic variables. Starting from the seminal paper by Romer and Romer (2004), this information is typically employed to capture the systematic component of monetary policy and isolate exogenous changes in the intended federal funds rate. However, considering point forecasts only might neglect key features of Federal Reserve's policymaking. As the minutes of FOMC meetings attest, the discussion of the economic outlook that precedes the monetary policy decisions is extensively based on considerations about higher moments of future outcomes. The latter are therefore likely to play a crucial role in FOMC deliberations, as Alan Greenspan's quote confirms. In particular, the uncertainty and skewness that characterize the expected paths for output growth and inflation may be important drivers of monetary policy decisions, although their intrinsically unobservable nature makes them difficult to quantify.

In this paper, I try to address this challenge by using quantile factor models to estimate the conditional distribution of Greenbook forecasts for output growth and inflation. Specifically, I employ the partial quantile regression approach proposed by Giglio et al. (2016), that provides a convenient setting to embed the large amount of information to which the Federal Reserve has access. This methodology allows to construct Fed-based indexes of uncertainty and skewness, that I then incorporate in an augmented version of the regression originally estimated by Romer and Romer (2004). The main takeaway from this analysis is that controlling for point forecasts only is not sufficient to purge FOMC decisions of their systematic component. Higher moments of Federal Reserve's internal projections are in fact found to capture important decision-making features. More in detail, a rise in the skewness of the forecast distribution of output growth and inflation rate is associated with a more accommodative monetary policy stance. To shed light on the theoretical mechanisms that drive this result, I study a simple optimal monetary policy problem under a non-linear weighting of probabilities. This exercise suggests that my empirical evidence is consistent with the optimal behavior of a central bank that sets the interest rate by assigning more weight to high-probability outcomes.

This finding leads to important implications for the identification of monetary policy shocks. If we exclusively control for point forecasts, a non-negligible share of changes in the intended federal funds rate might be erroneously considered as exogenous and this could therefore result into a misidentification of the monetary policy shocks and of their dynamic effects. I show that this is actually the case by evaluating the transmission of US monetary shocks over the period 1983-2007. When the monetary policy shock is identified by using Romer and Romer's (2004) specification, I find evidence of a quite strong price puzzle. On the contrary, when their baseline regression is augmented with uncertainty and skewness indexes, the price response is found to be more consistent with theoretical predictions. The improvements achieved by controlling for higher moments can also be appreciated by looking at the properties of the shock series itself. Compared to Romer and Romer (2004), the shock I recover shows a lower autocorrelation and is therefore less predictable given past information.

The estimated skewness of Fed's internal projections is also found to predict movements in interest rate futures over 30-minute windows around FOMC announcements. This implies that conditioning on higher moments might be crucial to fully characterize the signalling channel of monetary policy (Melosi, 2017; Miranda-Agrippino and Ricco, 2021). More specifically, this evidence is coherent with a scenario where FOMC policy decisions reveal central bank private information that is not only associated with central moments of expected economic outcomes, but that also refers to the risks surrounding them. In addition to this, I show that controlling for skewness leads to larger estimates of the effects on prices of central bank information shocks recovered through high-frequency identification.

The structure of the paper is as follows. Section 2 reviews the related literature. Section 3 presents the data and the econometric framework. Section 4 describes the Fed-based measures of uncertainty and skewness. Section 5 shows that skewness is an important explanatory factor for the monetary policy decisions taken by the FOMC, and explores the theoretical mechanism driving this finding. Section 6 introduces a higher moments robust measure of monetary policy shocks and evaluates its dynamic effects. Section 7 concludes.

2 Related Literature

This paper is closely related to Aruoba and Drechsel (2023), who employ text analysis methods on the Greenbook verbal information to produce sentiment indicators for almost 300 economic concepts, that are then incorporated in Romer and Romer's (2004) regression by using machine learning techniques. Coherently with my results, they show that going beyond Greenbook point forecasts improves the identification of monetary policy shocks. Despite these similarities, my work is significantly different from theirs. Rather than computing a unidimensional sentiment indicator, I disentangle between uncertainty and skewness, with only the latter that is found to be informative for the monetary policy decisions taken by the FOMC. Furthermore, I provide a specific theoretical mechanism through which skewness can influence the US monetary policy stance, and show that my findings are in line with the optimal behavior of an inflation targeting central bank that performs a non-linear weighting of probabilities. It should also be mentioned that, when jointly included in Romer and Romer's (2004) regression, only my quantile-based indicators of skewness turn out to be informative for FOMC decisions, while the coefficients associated to Aruoba and Drechsel's (2023) indexes for output growth and inflation rate are not statistically significant. My work also connects with Cieslak et al. (2022), who measure policy-makers' uncertainty by scrutinizing the sentences pronounced by each member of the FOMC. They conclude that policymakers' beliefs about higher moments of the economic distributions affect their hawkishness, with uncertainty that is found to play a prominent role.

My paper is also related to the literature that focuses on higher moments of macroeconomic variables. First, it connects with the large research on macroeconomic uncertainty, that can be generally defined as the expected volatility of macroeconomic series. Starting with Jurado et al. (2015), its role for business cycle fluctuations has been largely investigated (e.g. Angelini et al., 2019; Ludvigson et al., 2021; Carriero et al., 2021; Carriero and Volpicella, 2023), even though without reaching a widespread consensus. Over the last few years, empirical works have shifted the attention towards the study of macroeconomic risks. In particular, Adrian et al. (2019) show that risks around output growth are not balanced, stressing the importance of taking skewness into account. Since then, several studies have investigated the conditional skewness of a single series (Forni et al., 2021; Jensen et al., 2021; Castelnuovo and Mori, 2022; Loria et al., 2023), while Iseringhausen et al. (2023) propose an aggregate indicator of macroeconomic skewness, that is computed as the first principal component among a large number of individual measures. Differently from these contributions, my higher moments indicators are not based on the actual realization of macroeconomic series but on Federal Reserve's internal forecasts. In particular, I exploit the historical relationship between a large number of US macroeconomic and financial variables (McCracken and Ng, 2016) and Greenbook forecasts for output growth and inflation to characterize their conditional distribution and build indicators of uncertainty and skewness. Importantly, the aggregate measures I derive from the quantile factor model (as simple average of the individual indicators for output growth and inflation forecasts) exhibit a sizeable positive comovement with the indexes proposed by Jurado et al. (2015) and Iseringhausen et al. (2023). However, these alternative measures do not have any explanatory power for the policy decisions taken by the FOMC, while the predictive ability of my Fed-based skewness indicators is robust to including them as controls. This suggests that using Federal Reserve's internal projections plays a decisive role in building highly informative measures. Furthermore, my paper is related to Al-Nowaihi and Stracca (2002), who study optimal monetary policy under skewed risks and non-standard central bank loss functions. In this respect, I show that my empirical findings can be rationalized within their framework by incorporating a non-linear weighting of probabilities.

From a methodological point of view, my paper is connected with the literature on quantile regressions, pioneered by Koenker and Bassett (1978). After the paper by Adrian et al. (2019), this approach has established itself as a standard tool in empirical macroeconomics (Plagborg-Møller et al., 2020; Caldara et al., 2020; Lopez-Salido and Loria, 2022). Similarly to what I do in this paper, in particular, Adams et al. (2021) use quantile regressions to construct uncertainty and risks around the median projections from the Survey of Professional Forecasters. However, standard quantile regressions might be no longer consistent if the number of regressors is large relative to the sample size (see e.g. Belloni and Chernozhukov, 2011). Moreover, conditioning on many predictors may also overfit the data and weaken the estimation performance. Given the goals of my paper, these concerns are extremely relevant. Central banks have access to a large amount of information that informs their projections, and selecting a small subset of predictors is therefore not an easy task. To address this issue, I rely on quantile factor models to reduce the number of regressors, while preserving a rich informational content. More precisely, I use the partial quantile regression approach proposed by Giglio et al. (2016), that extends partial least squares to the quantile setting. This methodology constitutes a convenient framework to embed the large amount of information that is likely to influence the internal forecasts prepared by the staff of the Federal Reserve Board. For an alternative application of partial quantile regressions, see Schmitz (2023), who use this technique to evaluate how monetary policy shocks shape the conditional distribution of consumption growth.

A related line of research estimates the conditional distribution of macroeconomic variables by employing fully parametric models that feature time-varying volatility and/or skewness (e.g. Delle Monache et al., 2023; De Polis et al., 2023). As a robustness check, therefore, I build on Plagborg-Møller et al. (2020) and resort to a conditional heteroskedasticity model that assumes approximate sparsity by imposing a 'horseshoe' prior (see Carvalho et al., 2010). This enables to shrink several coefficents towards zero and thus delivers a parsimonious model that retains a small number of prominent predictors only. I show that the resulting measures of dispersion for Greenbook forecasts related to output growth and inflation are reconcilable with the uncertainty indicators obtained from the quantile factor model. In addition to this, the latter are also found to strongly comove with measures of forecast disagreement among FOMC members, computed by using the information in the Federal Reserve's Summary of Economic Projections (for other uses of this dataset, see Banternghansa and McCracken, 2009; Bennani et al., 2018).

Finally, this paper is strictly related to the literature on the identification of monetary shocks and, especially, to Romer and Romer (2004) (see Tenreyro and Thwaites, 2016; Coibion et al., 2017; Wieland and Yang, 2020, for more recent applications of their approach). In this respect, my main contribution consists in showing that conditioning on Greenbook point forecasts is not enough to capture the systematic component of monetary policy, and that controlling for higher moments allows to retrieve monetary shocks that are less predictable and generate theoretically coherent effects. This work also connects with the research that studies the reaction of financial markets to FOMC announcements (e.g. Kuttner, 2001; Gürkaynak et al., 2005) and that uses it to recover monetary policy and central bank information shocks (e.g. Gertler and Karadi, 2015; Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021). In particular, I show that movements in federal funds rate futures in a 30-minute window around FOMC announcements can be partially explained by the higher moments of Federal Reserve's internal forecasts. Such a finding relates this paper to the recent literature on the signalling channel of monetary policy (e.g. Melosi, 2017; Miranda-Agrippino and Ricco, 2021), since it suggests that a non-negligible share of the private information revealed by the FOMC policy decisions may be associated with the uncertainty and risks that surround the expected paths for output growth and inflation.

3 Estimating the Conditional Quantiles of Greenbook Forecasts

In this section, I present the data and review the partial quantile regression methodology (Giglio et al., 2016). Then, I use this approach to estimate the 10*th*, 50*th* and 90*th* conditional quantiles of Greenbook forecasts for output growth and inflation, that will constitute the basis to compute the indicators of uncertainty and skewness introduced in Section 4.

3.1 The Data

The Greenbook is a document prepared by the Federal Reserve Board staff prior to each FOMC meeting and contains forecasts for several macroeconomic indicators.[1] In this paper, I consider one-quarter-ahead projections for output growth and inflation, the two most important variables for Federal Reserve's policy decisions. The focus on short-term forecasts is motivated by their invariance with respect to assumptions about the future stance of monetary policy. The period I examine goes from November 1968 to December 2017. This is the largest possible sample, since Greenbook forecasts are released to the public with a five-years lag and are only available without interruptions from the end of 1968. For the rest of this paper, let gdp and π represent output growth and the inflation rate, respectively. Then, y_t^i, with $i = \{gdp, \pi\}$, will denote the one-quarter-ahead Greenbook forecast for variable i produced in month t.

In order to estimate their conditional quantiles, I consider the 128 US macroeconomic and financial series contained in McCracken and Ng's (2016) monthly dataset, that are stored in the vector Z_t.[2] In particular, to avoid using information that was not available at the time when the forecast was produced, I condition on Z_{t-1}, that contains the realization of the variables for the month preceding the one in which the Greenbook was prepared.

[1] It is worth noting that their frequency is thus not regular. The FOMC convenes in fact eight times a year from 1981 onwards, while meetings were montly till 1978 (in 1979 and 1980, they were instead 9 and 11, respectively).

[2] For a complete description of the variables, please refer to Appendix A.

3.2 Partial Quantile Regression

Before introducing the partiale quantile regression methodology by Giglio et al. (2016), let me first review quantile regression in the univariate case. Let y_t^i denote the Greenbook forecast for either output growth or inflation, and let z_{t-1} represent one of the lagged predictors contained in Z_{t-1}. The τ-th quantile of y_t^i conditional on z_{t-1} can then be defined as

$$Q_{y_t^i|z_{t-1}}(\tau|z_{t-1}) = F^{-1}_{y_t^i|z_{t-1}}(\tau|z_{t-1}) = \inf\{y^i : F_{y_t^i|z_{t-1}}(y^i|z_{t-1}) \geq \tau\} \tag{1}$$

where $F_{y_t^i|z_{t-1}}(y^i|z_{t-1})$ denotes the probability distribution function of y_t conditional on z_{t-1}. In a quantile regression of y_t^i on z_{t-1}, the regression slope β_τ is selected to minimize the quantile weighted absolute value of errors,

$$\hat{\beta}_\tau = \underset{\beta_\tau \in \mathbb{R}^k}{\arg\min} \sum_{t=1}^{T-h} \left(\tau \cdot \mathbf{1}_{(y_t^i \geq \beta_\tau z_{t-1})} |y_t^i - \beta_\tau z_{t-1}| + (1-\tau) \cdot \mathbf{1}_{(y_t^i < \beta_\tau z_{t-1})} |y_t^i - \beta_\tau z_{t-1}| \right) \tag{2}$$

where $\mathbf{1}_{(\cdot)}$ is the indicator function. Koenker and Bassett (1978) prove that the predicted value from regression (2) yields a consistent estimator of the τ-th quantile of y_t^i conditional on z_{t-1},

$$\hat{Q}_{y_t^i|z_{t-1}}(\tau|z_{t-1}) = \hat{\beta}_\tau z_{t-1} \tag{3}$$

Quantile regressions differ from ordinary least squares (OLS) estimation in two main respects. First, they minimize the sum of absolute errors, rather than the sum of squared errors. Second, they assign different weights to the error terms depending on whether they are above or below the quantile of interest. Over the last few years, a growing literature has adopted this approach on macroeconomic variables. Adrian et al. (2019), for instance, characterize the distribution of GDP growth conditional on the National Financial Conditions Index (NFCI).

Estimating the conditional distribution of Greenbook forecasts poses a non-trivial problem of variable selection. The staff of the Federal Reserve Board has access to a large amount of information and many variables might thus inform their projections. To address this issue, I employ quantile factor models, that offer a convenient setting to embed the high-dimensional information contained in Z_{t-1}. In general, quantile factor models assume that the τ-th quantile of y_t conditional on Z_{t-1} is a linear function of an unobservable univariate factor f_t,

$$Q_{y_t^i|Z_{t-1}}(\tau|Z_{t-1}) = f_t \alpha_\tau \tag{4}$$

Following Kelly and Pruitt (2015), I assume that the large cross-section of predictors Z_{t-1} has the following factor structure,

$$Z_{t-1} = \Lambda F_{t-1} + \varepsilon_{t-1} = \phi f_{t-1} + \psi g_{t-1} + \varepsilon_{t-1} \tag{5}$$

where ε_{t-1} are idiosyncratic measurement errors and F_{t-1} is a factor term that consists of two components: the subset f_{t-1} collects the factors that are allowed to influence the target variable y_t^i, while the subset g_{t-1} contains those that do not affect y_t^i but might instead drive the cross-section of regressors Z_{t-1}. In order to obtain f_{t-1} and recover the quantiles of y_t^i conditional on Z_{t-1}, I employ the partial quantile regression approach (Giglio et al., 2016). This methodology combines partial least squares and quantile regression by synthetizing the lagged predictors in the set Z_{t-1} according to their quantile covariation with the dependent variable. More in detail, it estimates the τ-th quantile of y_t^i conditional on Z_{t-1} through the following steps.

1. For $j = 1, \ldots, 128$, estimate univariate τ-th quantile regressions of y_t^i on a constant and $z_{t-1}^j \in Z_{t-1}$ to get slope estimates $\hat{\phi}_j$.

2. Compute the cross-sectional covariance of z_{t-1}^j and $\hat{\phi}_j$ for each period t to get the factor estimate $\hat{f}_{t-1}$. This amounts to retrieve it as a weighted average of individual predictors, with weights that depend on the predictive power from the first step,

$$\hat{f}_{t-1} = \sum_{j=1}^{N} (z_{t-1}^j - \bar{z}_{t-1})(\hat{\phi}_j - \bar{\phi}) \tag{6}$$

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

It is worth stressing that a consistent quantile factor estimate is calculated as linear combination of the elements of Z_{t-1}, with weights depending on their predictive power for the τ-th quantile of the target variable y_t^i. This implies that the resulting factors $\hat{f}_{t-1}$ differ for each combination of quantile/target variable. For a detailed analysis of the individual predictors that drive $\hat{f}_{t-1}$ as well as for a plot of the factors, please refer to Appendix A and B.

3.3 Conditional Quantiles of Greenbook Forecasts

In Figure 1, I display the conditional quantiles, for $\tau = \{0.1, 0.5, 0.9\}$, of Greenbook forecasts for output growth and inflation, estimated by using the partial quantile regression methodology. These quantiles are computed on the full sample and will constitute the starting point to derive the indexes of uncertainty and skewness introduced in Section 4 , that I will later use to estimate an augmented version of Romer and Romer's (2004) regression. For the real-time counterpart of the conditional quantiles in Figure 1, please refer to Appendix C.

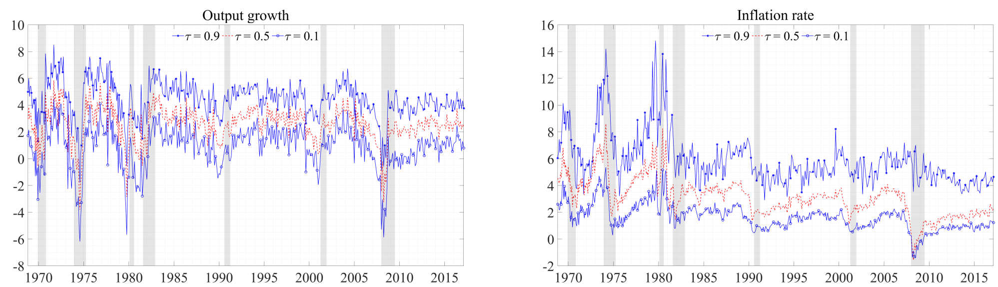

Figure 1: Conditional Quantiles of Greenbook Forecasts Over Time.

Using the full sample allows to include all the information available to us in the estimation and this is fundamental to properly characterize the conditional distribution of Greenbook forecasts and, in particular, of their tails. In the real-time analysis, for instance, the first part of the sample (that covers the Great Inflation of the 1970s and early 1980s) is not particularly informative for low quantiles of the inflation forecast distribution, since the estimation would be almost entirely based on events that belong to the right tail of the inflation realizations.

4 Greenbook Forecast Uncertainty and Skewness

Below, I use the conditional quantile estimates detailed in the previous section to build indexes of uncertainty and skewness based on Greenbook projections for output growth and inflation.

4.1 Measuring Uncertainty

For $i = \{gdp, \pi\}$, uncertainty is defined as the difference between the 90*th* and 10*th* quantile,

$$U_t^i = \hat{Q}_{y_t^i|Z_{t-1}}(0.9|Z_{t-1}) - \hat{Q}_{y_t^i|Z_{t-1}}(0.1|Z_{t-1}) \tag{7}$$

The resulting uncertainty indicators are displayed in Figure 2. In both cases, they spike during recessions, with peaks reached in 1975 for output growth and in 1980 for inflation. In Appendix B, I compare these two series with measures of forecast disagreement among FOMC members and compute an aggregate indicator of macroeconomic uncertainty, that turns out to display a large positive correlation with Jurado et al.'s (2015) index. Furthermore, I show that estimating

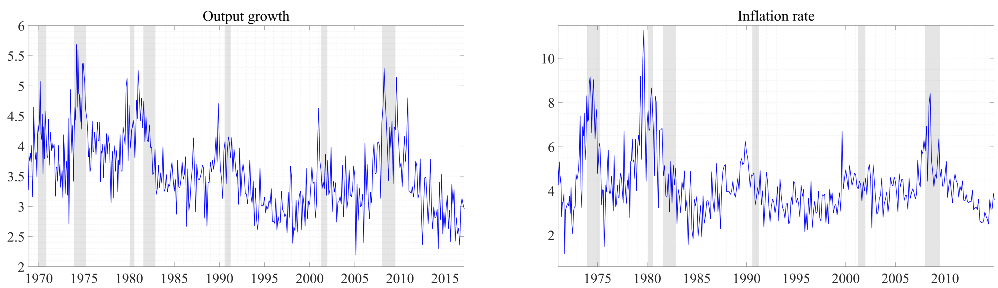

Figure 2: Greenbook Forecast Dispersion for Output Growth and Inflation Rate.

a parametric model based on Bayesian shrinkage techniques (i.e. 'horseshoe' prior) generates measures of uncertainty that are consistent with those described in this section.

4.2 From Greenbook Forecast Uncertainty to Skewness

Following Forni et al. (2021), I decompose Greenbook forecast uncertainty into an upside and a downside component, that will provide the basis to derive indicators of skewness. First, note that the definition of uncertainty introduced in equation (7) can be rewritten as,

$$U_t^i = [\hat{Q}_{y_t^i|Z_{t-1}}(0.9|Z_{t-1}) - \hat{Q}_{y_t^i|Z_{t-1}}(0.5|Z_{t-1})] + [\hat{Q}_{y_t^i|Z_{t-1}}(0.5|Z_{t-1}) - \hat{Q}_{y_t^i|Z_{t-1}}(0.1|Z_{t-1})] \quad (8)$$

In other words, the indexes of Greenbook forecast uncertainty U_t^i can be decomposed into the sum of upside and downside uncertainty, $U_t^{i,u}$ and $U_t^{i,d}$, where

$$U_t^{i,u} = \hat{Q}_{y_t^i|Z_{t-1}}(0.9|Z_{t-1}) - \hat{Q}_{y_t^i|Z_{t-1}}(0.5|Z_{t-1}) \quad (9)$$

$$U_t^{i,d} = \hat{Q}_{y_t^i|Z_{t-1}}(0.5|Z_{t-1}) - \hat{Q}_{y_t^i|Z_{t-1}}(0.1|Z_{t-1}) \quad (10)$$

The resulting indexes of upside and downside uncertainty are plotted in Appendix B. Skewness is then measured by deriving the absolute Kelley index (Kelley, 1947), defined as,

$$S_t^i = U_t^{i,u} - U_t^{i,d} \quad (11)$$

Figure 3 plots the skewness indicators for Greenbook forecasts. The measure for output growth shows a more erratic behavior than the one for inflation. In the latter case, the index experiences an important spike during the Great Recession. In Appendix B, I show that the aggregate index

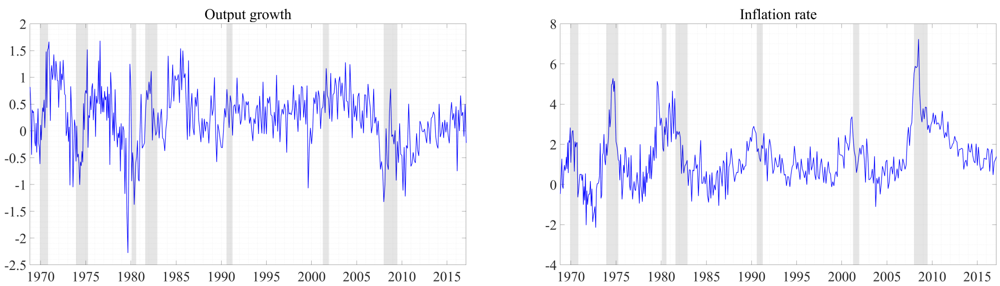

Figure 3: Greenbook Forecast Skewness for Output Growth and Inflation Rate.

of skewness obtained by averaging across S_t^{gdp} and S_t^{π} shows a large positive correlation with Iseringhausen et al.'s (2023) indicator of macroeconomic skewness and with the first principal component of the sentiment indicators computed by Aruoba and Drechsel (2023).

5 Monetary Policy Decisions and Higher Moments of Greenbook Forecasts

This section evaluates whether higher moments of Greenbook forecasts may be informative for the US monetary policy stance. Specifically, I assess if Fed-based indicators of uncertainty and skewness about future output growth and inflation might help explaining FOMC deliberations beyond the point forecasts that are typically used in the estimation of monetary policy rules.

To test this hypothesis, I augment Romer and Romer's (2004) regression by incorporating the indicators derived in Section 4. Unlike the original paper, that covers the period 1969-1996, I consider the sample 1983-2007. This is a rather common choice in the literature that revisits Romer and Romer (2004), given that it allows to exclude the period of nonborrowed reserves targeting (from 1979 to 1983) as well as the post-2008 unconventional monetary policy.

5.1 Augmenting Romer and Romer's (2004) Regression

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

$$\begin{aligned}\Delta ff_t = \alpha + ff_t + \sum_{j=-1}^{2} \phi_j F_t^{gdp,j} + \sum_{j=-1}^{2} \theta_j F_t^{\pi,j} + \beta_0 F_t^{u,0} + \\ \sum_{j=-1}^{2} \gamma_j [F_t^{gdp,j} - F_{t-1}^{gdp,j}] + \sum_{j=-1}^{2} \vartheta_j [F_t^{\pi,j} - F_{t-1}^{\pi,j}] + \varepsilon_T^m \qquad (12)\end{aligned}$$

where Δff_t denotes the change in the intended funds rate decided in the FOMC meeting held in month t; ff_t is the level of the intended federal funds rate prevailing before the FOMC meeting took place; $F_t^{i,j}$, for $i = \{gdp, \pi\}$, is the Greenbook projection for variable i at quarter j while $[F_t^{i,j} - F_{t-1}^{i,j}]$ is the forecast revision for variable i at quarter j. The residual of regression (12), denoted by ε_d^m, is typically considered to be free of any endogenous movement and is therefore taken as an exogenous measure of monetary policy shocks.

The implicit assumption behind Romer and Romer's (2004) regression is that Greenbook point forecasts embed all the information that is necessary to capture the systematic component of monetary policy. In this paper, I question this view and evaluate whether the monetary policy actions taken by the FOMC may also be explained by higher moments of Greenbook forecasts. In Table 1, I show the result of this analysis. In particular, the first column displays the findings obtained by using Romer and Romer's (2004) baseline specification. The R^2 amounts to 0.49 and suggests therefore that a large share of the movements in the intended funds rate is actually explained by the forecasts for future output growth and inflation that are made available to the policymakers. It should be noted that the R^2 found by Romer and Romer (2004) for the sample 1969-1996 is much smaller and only amounts to 0.29. This difference is not surprising and is explained by the exclusion of periods where (12) does not represent a good approximation of the FOMC decision-making process. The second column of Table 1 reports the results obtained when (12) is augmented by incorporating the indicators of uncertainty and skewness for output growth and inflation projections. While uncertainty is not found to have explanatory power for the movements in the intended federal funds rate, the coefficients related to skewness are large and statistically significant. This is an important finding, since it suggests that a non-negligible share of changes in the intended funds rate may erroneously be considered as exogenous if we do not control for higher moments. In the last column, I enlarge the previous specification by including the first lag of the uncertainty and skewness measures.

In Table 2, I control for alternative proxies of higher moments taken from the literature. In particular, I augment the regression by including Jurado et al. (2015) macroeconomic, financial and real uncertainty, Iseringhausen et al. (2023) macroeconomic skewness, and the Greenbook text-based sentiment indicators for output growth and inflation derived by Aruoba and Drechsel (2023). Importantly, none of them is found to be a significant predictor for the changes in the

	(1) Δff	(2) Δff	(3) Δff
Constant	0.07 (0.08)	0.07 (0.12)	0.25 (0.15)
Pre-meeting intended funds rate	-0.06*** (0.01)	-0.06*** (0.01)	-0.06*** (0.01)
Forecasted inflation -1	0.02 (0.02)	0.02 (0.02)	0.02 (0.01)
Forecasted inflation 0	0.06*** (0.02)	0.06*** (0.02)	0.05*** (0.02)
Forecasted inflation +1	0.03 (0.04)	0.02 (0.04)	0.00 (0.04)
Forecasted inflation +2	0.03 (0.04)	0.03 (0.04)	0.04 (0.05)
Change in inflation forecast -1	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Change in inflation forecast 0	-0.07** (0.03)	-0.07** (0.03)	-0.06** (0.03)
Change in inflation forecast +1	0.01 (0.05)	0.02 (0.05)	0.02 (0.05)
Change in inflation forecast +2	0.01 (0.06)	0.02 (0.06)	0.03 (0.06)
Forecasted output growth -1	0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)
Forecasted output growth 0	0.06*** (0.01)	0.04*** (0.02)	0.03** (0.02)
Forecasted output growth +1	0.02 (0.02)	0.01 (0.02)	0.01 (0.02)
Forecasted output growth +2	-0.02 (0.01)	-0.00 (0.02)	0.02 (0.02)
Revision in output growth forecast -1	0.01 (0.02)	0.02 (0.01)	0.03** (0.01)
Revision in output growth forecast 0	0.04* (0.02)	0.04** (0.02)	0.05** (0.02)
Revision in output growth forecast +1	0.03 (0.02)	0.03 (0.02)	0.04** (0.02)
Revision in output growth forecast +2	0.04 (0.03)	0.04 (0.03)	0.02 (0.02)
Forecasted unemployment rate 0	-0.05*** (0.01)	-0.04** (0.02)	-0.03 (0.02)
Uncertainty - Inflation		0.03 (0.03)	0.04 (0.03)
Uncertainty - Output growth		0.01 (0.03)	0.01 (0.03)
Skewness - Inflation		-0.10*** (0.04)	-0.10*** (0.03)
Skewness - Output growth		-0.09* (0.05)	-0.10** (0.05)
Lagged uncertainty - Inflation			-0.02 (0.02)
Lagged uncertainty - Output growth			-0.01 (0.04)
Lagged skewness - Inflation			-0.06** (0.03)
Lagged skewness - Output growth			-0.12*** (0.04)
R^2	0.49	0.52	0.56
Adjusted R^2	0.44	0.46	0.49
Number of observations	200	200	200

Table 1: Augmenting Romer and Romer's (2004) Regression.

Notes: HAC standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01. Estimation sample: 1983-2007.

federal funds rate deliberated by the FOMC. On the other hand, the coefficients associated to my quantile-based indexes of skewness are statistically significant even when these alternative

	(1) Δff	**(2)** Δff
Constant	Yes	Yes
Pre-meeting intended funds rate	Yes	Yes
Greenbook forecasts	Yes	Yes
Uncertainty - Inflation	0.04 (0.03)	0.04 (0.03)
Uncertainty - Output growth	0.01 (0.03)	0.02 (0.03)
Skewness - Inflation	-0.10*** (0.03)	-0.09** (0.04)
Skewness - Output growth	-0.10** (0.05)	-0.09* (0.05)
Lagged uncertainty - Inflation	-0.02 (0.02)	-0.02 (0.03)
Lagged uncertainty - Output growth	-0.01 (0.04)	-0.01 (0.04)
Lagged skewness - Inflation	-0.06** (0.03)	-0.05* (0.03)
Lagged skewness - Output growth	-0.12*** (0.04)	-0.11** (0.04)
Macroeconomic uncertainty JLN		-0.41 (0.60)
Real uncertainty JLN		0.73 (0.81)
Financial uncertainty JLN		-0.10 (0.14)
Macroeconomic skewness IPT		-0.00 (0.01)
Fed sentiment AD - Inflation		-0.00 (0.02)
Fed sentiment AD - Output growth		-0.00 (0.02)
R^2	0.56	0.57
Adjusted R^2	0.49	0.48
Number of observations	200	200

Table 2: Controlling for Alternative Higher Moments Indicators.

Notes: JLN, IPT and AD stand for Jurado et al. (2015), Iseringhausen et al. (2023) and Aruoba and Drechsel (2023), respectively. HAC standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01. Estimation sample: 1983-2007.

indicators of higher moments are incorporated in the regression. This suggests that using Fed's internal information plays a decisive role in building measures that have a strong explanatory power for the monetary policy decisions taken by the FOMC.

5.2 Investigating the Mechanism

The empirical findings discussed above suggest that skewness is an important decision-making factor. Specifically, an increase in the skewness of the distribution of future output growth and inflation seems to lead to a more accommodative monetary policy stance. Understanding the mechanisms driving this evidence is however not straightforward. To clarify this point, Figure 5 plots two inflation density forecasts that have the same mean (set equal to zero for simplicity) but different skewness.[3] An increase in skewness triggers two simultaneous effects: on the one hand, it magnifies the probability of high-inflation events (left panel); on the other, it shifts the probability mass towards deflationary outcomes (right panel).

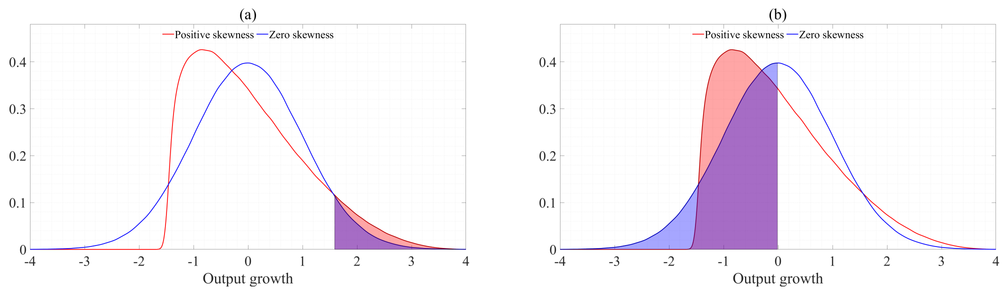

Figure 4: Skewness and Monetary Policy Decisions: An Example.

In this section, I show that my empirical results can be reconciled with the optimal behavior of an inflation targeting central bank. This exercise will require a departure from the standard quadratic loss function with a linear weighting of probability (see, for instance, Svensson and Woodford, 2003). In this case, as detailed below, the certainty equivalence principle holds and uncertainty about the state of the economy has no effects on the optimal policy rate. By using Al-Nowaihi and Stracca's (2002) framework, I will show that my empirical findings are instead consistent with optimal monetary policy under quadratic preferences and non-linear weighting of probabilities. In this scenario, the optimal policy rate will indeed be inversely related to the degree of skewness that characterizes the distribution of future inflation (or output growth).

[3]The exact same argument would apply to output growth.

5.2.1 A Simple Optimal Monetary Policy Problem

Following Al-Nowaihi and Stracca (2002), let us consider an economy that is described by an IS curve and a backward-looking Phillips curve.

The IS curve can be expressed as follows,

$$y_t = \alpha y_{t-1} - \eta(i_t - \pi_t) + \varepsilon_t^y \tag{13}$$

where y_t is the output gap; i_t is the nominal interest rate; π_t is the inflation rate; ε_t^y is the output gap shock; $E_t\varepsilon_t^y = 0$; $0 < \alpha < 1$ and $\eta > 0$. The Phillips curve is instead given by,

$$\pi_{t+1} = \delta\pi_t + \gamma y_t + \varepsilon_{t+1}^\pi \tag{14}$$

where ε_{t+1}^π is a cost-push shock; $E_t\varepsilon_{t+1}^\pi = 0$; $0 < \delta < 1$ and $\gamma > 0$.[4] Note that ε_t^y and ε_{t+1}^π are zero mean but no further assumptions are made on their distribution. Combining (13) and (14),

$$\pi_{t+1} = \theta\pi_t + \kappa y_{t-1} - \lambda i_t + \varepsilon_{t+1} \tag{15}$$

where $\theta = \delta + \gamma\eta$, $\kappa = \gamma\alpha$ and $\lambda = \gamma\eta$. Note that $\varepsilon_{t+1} = \gamma\varepsilon_t^y + \varepsilon_{t+1}^\pi$ is a zero mean disturbance that can be non-Normal and non-symmetrically distributed. Letting $z_t = \theta\pi_t + \kappa x_{t-1}$,

$$\pi_{t+1} = z_t - \lambda i_t + \varepsilon_{t+1} \tag{16}$$

Let us consider a simple optimal monetary policy problem under discretion, where the central bank sets the nominal interest rate i_t to minimize the following intertemporal loss function Λ,[5]

$$\Lambda = E_t \sum_{j=1}^{\infty} \beta^{j-1} L(\pi_{t+j}) \tag{17}$$

$L(\pi)$ captures the central bank's preferences while $0 < \beta < 1$. The law of motion in (16) acts

[4] I assume no drift for the inflation process. Combined with $\alpha < 1$, this implies zero inflation at the steady state.

[5] In this exercise, as in Al-Nowaihi and Stracca (2002), I do not consider the case when the central bank also targets the output gap.

as a constraint in the minimization of Λ. Since it is recursive and i_t can only affect one-period-ahead inflation, the problem can be reduced to the minimization of $E_t L(\pi_{t+1})$. Let us consider optimal monetary policy under standard quadratic preferences,

$$E_t L(\pi_{t+1}) = E_t \pi_{t+1}^2 \tag{18}$$

By plugging (18) in the objective function, we obtain:

$$E_t L(\pi_{t+1}) = E_t(z_t - \lambda i_t + \varepsilon_{t+1})^2 = E_t(z_t^2 + \lambda^2 i_t^2 + \varepsilon_{t+1}^2 - 2z_t\lambda i_t + 2z_t\varepsilon_{t+1} - 2\lambda i_t \varepsilon_{t+1}) \tag{19}$$

By solving the first order condition,

$$\frac{\partial E_t L(\pi_{t+1})}{\partial i_t} = 2\lambda^2 i_t - 2z_t\lambda - 2\lambda E_t \varepsilon_{t+1} = 0 \tag{20}$$

Given that $E_t \varepsilon_{t+1} = 0$, the solution to the minimization problem is,

$$i_t = \frac{z_t}{\lambda} = \frac{\theta\pi_t + \kappa x_{t-1}}{\lambda} \tag{21}$$

This is the classic certainty equivalence result arising under quadratic preferences: the optimal i_t does not depend on the probability distribution of ε_{t+1}. In this scenario, the skewness of the distribution of future inflation does not impact the optimal policy rate set by the central bank.

5.2.2 Nonlinear Weighting of Probabilities

Let us now introduce a central bank that does not minimize $E_t L(\pi_{t+1})$, but $\tilde{E}_t L(\pi_{t+1})$:

$$\tilde{E}_t L(\pi_{t+1}) = \int L(\pi_{t+1})\delta(P(\pi_{t+1}))d\pi_{t+1} \tag{22}$$

where P is the probability density function of π_{t+1} and δ is a weighting function that satisfy $0 \leq \delta(P(\pi_{t+1})) \leq 1$. Note that the function δ preserves symmetry, since it is a function of P and not of π_{t+1}. Hence, $\delta(P(\pi_{t+1})) = \delta(P(-\pi_{t+1}))$ if $P(\pi_{t+1}) = P(-\pi_{t+1})$. The expression in (22) generates an expected value for $L(\pi_{t+1})$, computed according to the transformed probability law $\delta(P)$. Following Tversky and Kahneman (2002), let us consider the functional form:

$$\delta(P) = \frac{P^{\omega}}{[P^{\omega} + (1-P)^{\omega}]^{\frac{1}{\omega}}} \tag{23}$$

where $\omega > 0$. This function includes the linear weighting when $\omega = 1$. The weighting function is instead first concave and then convex for $0 < \omega < 1$, while it is first convex and then concave for $1 < \omega < 2$. For $\omega > 2$, the weighting function is instead strictly convex.

Let us assume that the central bank has quadratic preferences but weighs probabilities in a nonlinear way. In other words, at time t, the central bank has to select the nominal interest rate i_t that minimizes the following loss function,

$$\tilde{E}_t \pi_{t+1}^2 = \tilde{E}_t (z_t - \lambda i_t + \varepsilon_{t+1})^2 \tag{24}$$

Developing the quadratic term in parentheses leads to:

$$\tilde{E}_t \pi_{t+1}^2 = \tilde{E}_t (z_t - \lambda i_t + \varepsilon_{t+1})^2 = \tilde{E}_t (z_t^2 + \lambda^2 i_t^2 + \varepsilon_{t+1}^2 - 2 z_t \lambda i_t + 2 z_t \varepsilon_{t+1} - 2\lambda i_t \varepsilon_{t+1}) \tag{25}$$

By solving the first order condition, we obtain,

$$\frac{\partial \tilde{E}_t L(\pi_{t+1})}{\partial i_t} = 2\lambda^2 i_t - 2 z_t \lambda - 2\lambda \tilde{E}_t \varepsilon_{t+1} = 0 \tag{26}$$

This implies that the optimal monetary policy rate is given by,

$$i_t = \frac{z_t}{\lambda} + \frac{\tilde{E}_t \varepsilon_{t+1}}{\lambda} \tag{27}$$

that corresponds to the canonical solution $i_t = \frac{z_t}{\lambda}$ if and only if $\tilde{E}_t \varepsilon_{t+1} = 0$. Due to the symmetry preservation of $\delta(P)$, this holds true when the probability distribution of ε_{t+1} is symmetric. If the distribution of ε_{t+1} is asymmetric and $\omega \neq 1$, the nonlinear weighting will instead be non-neutral and $\tilde{E}_t \varepsilon_{t+1} \neq E_t \varepsilon_{t+1} = 0$. In this case, the probability distribution of ε_{t+1} will not be irrelevant and the principle of certainty equivalence will not hold. In other words, combining a nonlinear weighting of probabilities and a skewed probability distribution for ε_{t+1} results in a departure from the certainty equivalence principle.

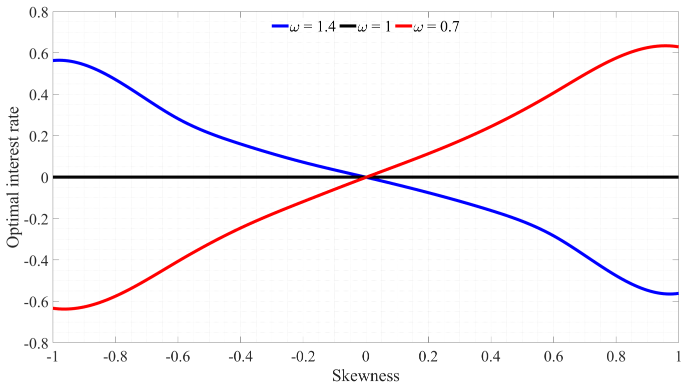

Figure 5: Optimal Interest Rate for Different Levels of Skewness of the Distribution of ε_{t+1}.

Figure 6 shows the optimal interest rate for various degrees of skewness of the distribution of ε_{t+1} and under three different scenarios: (i) $\omega < 1$ (greater weight to low-probability events); (ii) $\omega = 1$ (linear weight); (iii) $\omega > 1$ (greater weight to high-probability events).[6] In the latter case, the optimal policy rate is inversely related to the level of skewness of the distribution of future inflation, in line with the empirical evidence discussed in Section 5.1. Hence, the FOMC decision-making process appears to be reconcilable with a situation in which high-probability outcomes are weighted more than those with low-probability. In other words, the value of ω for the FOMC seems to be larger than 1. In the literature on decision-making under uncertainty, ω is typically estimated to be around 0.7 (e.g. Tversky and Kahneman, 2002). Thus, my results suggest that central banks may weight probability in a quite different way than private agents.

[6] The simulation is run by setting $\alpha = 0.645$, $\gamma = 0.5$, $\eta = 0.9$ and $\delta = 0.9$ (this implies $\lambda = 0.45$, $\kappa = 0.32$ and $\theta = 1.22$). π_t and x_{t-1} are set equal to their steady state value of zero.

In Appendix E, I show that employing a nonlinear weighting of probability is not the only way to rationalize the empirical findings in Section 5.1. An absolute loss function leads to similar conclusion about the relationship between skewness and optimal policy rate.

6 Higher Moments and the Transmission of Monetary Policy

This section studies the transmission of the monetary policy shocks I recover when the original regression of Romer and Romer (2004) is enlarged by including higher moments. Specifically, I consider the residuals of the third regression in Table 1, which I will denote as higher moments robust (HMR) monetary policy shocks. Furthermore, it also evaluates the relationship between higher moments and high-frequency monetary surprises, unveiling potential implications for the information channel of monetary policy.

6.1 Higher Moments Robust (HMR) Monetary Policy Shocks

In Figure 6, I compare the HMR shock with the original shock identified by Romer and Romer (2004). Unsurprisingly, the latter displays higher volatility, due to the larger share of variation in the federal funds rate that is regarded as exogenous when higher moments are omitted from (12). In Appendix F, I show that the HMR shock features lower autocorrelation and is therefore less predictable given past information.

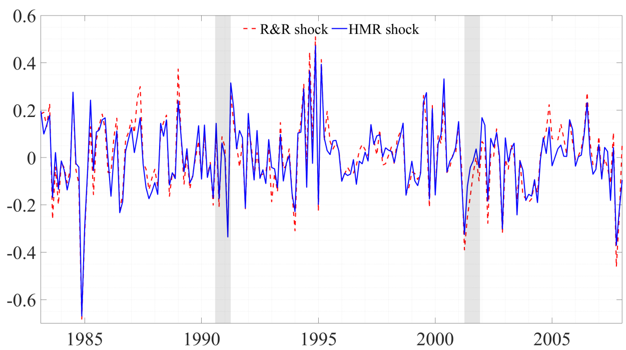

Figure 6: Romer and Romer's (2004) Shock *vs* Higher Moments Robust (HMR) Shock.

Below, I employ local projections (Jordà, 2005) to compare the transmission of HMR and Romer and Romer's (2004) shocks.[7] In particular, for $h = 0,\dots,30$ and $i = \{gdp_t, pi_t, ebp_t, ff_t\}$, I estimate this regression at the monthly frequency,

$$y^i_{t+h} = \gamma^{(h)} + \sum_{l=1}^{12} \alpha_l^{(h)} X'_{t-l} + \sum_{j=0}^{2} \beta_j^{(h)} \varepsilon^m_{t-j} + u_t \tag{28}$$

where $X_t = \left[gdp_t, pi_t, ebp_t, ff_t\right]$ and gdp_t is the log of real GDP; pi_t is the log of GDP deflator; ebp_t is Gilchrist and Zakrajšek's (2012) excess bond premium and ff_t is the federal funds rate.[8] The monetary policy shock is instead denoted by ε^m_t and, according to the case, is selected as the HMR shock or Romer and Romer's (2004) shock. Specifically, the coefficient $\hat{\beta}_0^{(h)}$ is the one capturing the response of y_t to ε^m_t at time $t+h$ and is thus the main object of interest.[9]

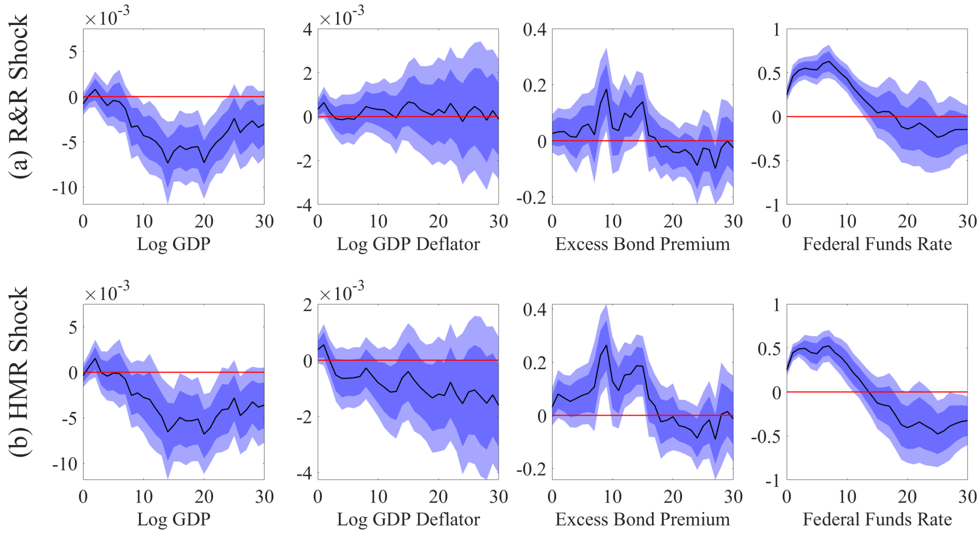

Figure 7: Dynamic Effects of R&R Shock *vs* HMR Shock Using Local Projections.

Notes: Solid line is the response calculated by local projections. Light and dark blue bands are 68% and 90% confidence intervals for the coefficients of local projections responses. Monetary policy shocks are normalized to induce a 25 basis points rise in ff_t.

[7] In Appendix H, I show that using the two shocks as internal instruments in a SVAR yields very similar results.

[8] The monthly series for real GDP and GDP deflator are constructed by using interpolation of the corresponding quarterly series, as in Bernanke and Mihov (1998). In particular, real GDP is interpolated by employing industrial production, while the GDP deflator is interpolated by using the consumer price index and the producer price index.

[9] To control for the short-term autocorrelation in Romer and Romer's shock, I include the first two lags of ε^m_{t-j}.

As shown in Figure 7, HMR and Romer and Romer's (2004) shocks generate quite similar effects on output. In both cases, consistently with theoretical predictions, US economic activity is found to decrease after a monetary contraction. On the other hand, the transmission to prices is dramatically different between the two shocks. Romer and Romer's (2004) shock triggers a puzzling (although only weakly significant) increase in prices, while the HMR shock induces a persistent and statistically significant (at least at the 68% confidence level) decline in the GDP deflator. Furthermore, conditioning on higher moments of Greenbook projections appears also to be helpful in recovering monetary policy shocks that have theoretically consistent effects on credit markets. The positive and strongly significant response of the excess bond premium to a contractionary HMR shock is in fact coherent with the credit channel of monetary policy, that has been recently documented by many empirical works (e.g. Gertler and Karadi, 2015).

6.2 Higher Moments and the Central Bank Information Channel

Below, I investigate whether higher moments of expected economic outcomes might also play a role for the information channel of monetary policy. In particular, I assess if the uncertainty and skewness indicators introduced in Section 4 are able to predict the movements in three-month-ahead federal funds rate futures over 30-minute windows around FOMC announcements.

More in detail, I estimate an augmented version of Miranda-Agrippino and Ricco's (2021) regression, who originally project high-frequency monetary surprises on Greenbook forecasts for output growth, inflation and unemployment (and on their revisions, as Romer and Romer, 2004) to derive an informationally robust instrument for the identification of monetary policy shocks. In particular, they estimate the following regression at the FOMC frequency,

$$\Delta FF4_t^{hf} = \alpha + \sum_{j=-1}^{2} \phi_j F_t^{gdp,j} + \sum_{j=-1}^{2} \theta_j F_t^{\pi,j} + \beta_0 F_t^{u,0} + \\ \sum_{j=-1}^{2} \gamma_j [F_t^{gdp,j} - F_{t-1}^{gdp,j}] + \sum_{j=-1}^{2} \vartheta_j [F_t^{\pi,j} - F_{t-1}^{\pi,j}] + MPI_t^{FF4} \quad (29)$$

where $\Delta FF4_t^{hf}$ denotes the change in the three-month-ahead federal funds rate futures over a 30-minute window around the FOMC announcement held in month t. The goal of this regression is to take the so-called ‘central bank information channel’ into account. This phenomenon has been documented by a large literature (see Miranda-Agrippino, 2016, Melosi, 2017, Nakamura and Steinsson, 2018, Cieslak and Schrimpf, 2019, Jarozinski and Karadi 2020) and consists in the extraction by market participants of news about the future economic outlook from monetary announcements. By conditioning on central bank projections, regression (29) aims therefore at purging the monetary policy surprises from the confounding factors that are generated by the release of central bank private information and at retrieving a robust instrument MPI_t^{FF4}. On the other hand, the fitted value from regression (29), that I will denote by $INFO_t^{FF4}$, is taken as an instrument for the identification of central bank information shocks.[10]

My primary contribution to this literature consists in showing that the estimated uncertainty and skewness of Greenbook projections have a non-negligible explanatory ability for monetary policy surprises. This result, as displayed in the third column of Table 3, is robust to controlling for Jurado et al.’s (2015) uncertainty indicators, Aruoba and Drechsel’s (2023) sentiments and Iseringhausen et al.’s (2023) skewness. Specifically, over the period 1983-2007, the skewness of output growth and inflation forecasts appears to play a crucial role. This result is consistent with the one obtained for the FOMC policy decisions and the sign of the coefficients is the same as in Table 1. On the contrary, when the regression spans the sample 1983-2008, the uncertainty related to Greenbook forecasts for inflation gains an important explanatory power. To explain this result, it is worth pointing out that the FOMC eased the monetary policy stance by cutting 225 basis points in 2008. These policy decisions contributed to generate an environment where views about future inflation outlook were quite mixed. As different policy statements confirm, although downside risks to output growth (and hence to inflation) were seen as prominent, the loosening monetary policy triggered upside risks to inflation that were of significant concern to

[10]Miranda-Agrippino and Ricco (2021) also regress MPI_t^{FF4} and $INFO_t^{FF4}$ on its own lagged values, in order to obtain high-frequency instruments that are purged from autocorrelation.

	(1) $\Delta FF4^{hf}$	(2) $\Delta FF4^{hf}$	(3) $\Delta FF4^{hf}$
Constant	0.01	-0.15	-0.04
	(0.03)	(0.12)	(0.10)
Forecasted inflation -1	-0.01	-0.01	-0.01*
	(0.01)	(0.01)	(0.01)
Forecasted inflation 0	0.01**	0.02**	0.01**
	(0.01)	(0.01)	(0.01)
Forecasted inflation +1	-0.01	-0.01	-0.02*
	(0.01)	(0.01)	(0.01)
Forecasted inflation +2	-0.00	-0.01	0.02*
	(0.02)	(0.01)	(0.01)
Change in inflation forecast -1	-0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Change in inflation forecast 0	-0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)
Change in inflation forecast +1	0.01	0.01	0.04**
	(0.02)	(0.02)	(0.02)
Change in inflation forecast +2	0.01	0.02	-0.02*
	(0.02)	(0.02)	(0.01)
Forecasted output growth -1	-0.01**	-0.01***	-0.01**
	(0.00)	(0.00)	(0.00)
Forecasted output growth 0	0.01***	0.01**	0.01*
	(0.01)	(0.01)	(0.01)
Forecasted output growth +1	0.00	-0.00	0.00
	(0.01)	(0.01)	(0.01)
Forecasted output growth +2	0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)
Revision in output growth forecast -1	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.01)
Revision in output growth forecast 0	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Revision in output growth forecast +1	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Revision in output growth forecast +2	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)
Forecasted unemployment rate 0	-0.01	0.00	-0.00
	(0.00)	(0.01)	(0.00)
Skewness - Inflation		-0.02*	-0.04
		(0.01)	(0.05)
Skewness - Output growth		-0.03*	-0.10*
		(0.02)	(0.06)
Uncertainty - Inflation		-0.01	-0.02***
		(0.01)	(0.01)
Uncertainty - Output growth		0.01	-0.00
		(0.01)	(0.01)
Controls	No	Yes	Yes
R^2	0.19	0.26	0.30
Adjusted R^2	0.08	0.09	0.14
Estimation sample	1983-2007	1983-2007	1983-2008
Number of observations	144	144	152

Table 3: Higher Moments and Monetary Policy Surprises.

Notes: Controls include macroeconomic, real and financial uncertainty (Jurado et al., 2015), an index of macroeconomic skewness (Iseringhausen et al., 2023) and Fed sentiment indicators for output growth and inflation rate (Aruoba and Drechsel, 2023). HAC standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

the FOMC. The findings reported in Table 3 suggest that this high inflation uncertainty might have been actually transmitted to market participants.[11]

This evidence points therefore towards the existence of a ‘higher moments channel’ in the transmission of Federal Reserve private information. It is in fact reconcilable with a scenario where the signals conveyed by FOMC decisions are not only associated with central moments of expected economic outcomes, but also refer to the uncertainty and risks that surround them. Such a finding opens the door to implications for the high-frequency identification of monetary policy and central bank information shocks. In Appendix D, specifically, I show that part of the autocorrelation in MPI_t^{FF4}, that Miranda-Agrippino and Ricco (2021) strip away by projecting it on its lagged values, can be reduced by controlling for uncertainty and skewness.

7 Conclusion

In this paper, I show that higher moments of expected economic outcomes are crucial drivers of the monetary policy decisions taken by the FOMC. My main finding is that skewness captures important decision-making features, that affect the US monetary policy stance beyond the point forecasts typically used in policy rule estimates (e.g. Romer and Romer, 2004). In particular, an increase in the skewness of the distribution of expected output growth and inflation rate is associated with a more accommodative monetary policy stance. To shed light on the theoretical mechanisms that drive these findings, I study a simple optimal monetary policy problem under non-linear weighting of probability. This exercise shows that my empirical results are coherent with the optimal behavior of an inflation targeting central bank that sets the interest rate by assigning more weight to high-probability outcomes.

This finding leads to important implications for the identification of monetary policy shocks. Without conditioning on the skewness of Federal Reserve forecasts, a non-negligible share of changes in the federal funds rate may erroneously be considered as exogenous and the effects of

[11] Although to a lesser extent, Appendix D.1 shows that inflation uncertainty gains predictive power also for the monetary policy decisions when the sample is extended to 2008.

monetary shocks might thus be misidentified. I argue that this is indeed the case by studying the transmission of US monetary policy over the period 1983-2007. When monetary policy shocks are identified by using Romer and Romer's (2004) regression, US monetary contractions are found to generate rather puzzling effects, particularly on prices. On the other hand, when it is augmented with indicators of uncertainty and skewness, the resulting monetary shocks display lower autocorrelation and generate conventional effects on the economy. Furthermore, higher moments of Fed's internal projections are also found to be helpful in explaining the movements in three-month-ahead federal funds rate futures during a 30-minute window around the FOMC announcements. This evidence is consistent with the existence of a 'higher moments channel' for the transmission of central bank information, given that it suggests that FOMC decisions convey signals that are not only related to central moments of expected economic outcomes, but also to the uncertainty and the risks surrounding them.

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A Quantile Factor Model

A.1 McCracken and Ng's (2016) Dataset

This section provides information about the 128 macroeconomic and financial series contained in McCracken and Ng's (2016) monthly dataset, that can be divided into eight groups: interest and exchange rates; labor market; housing; consumption, orders and inventories; money and credit; output and income and prices. The number shown in the column TCODE denotes one of the following data transformation for a series x: (1) no transformation; (2) Δx_t; (3) $\Delta^2 x_t$; (4) $\log(x_t)$; (5) $\Delta \log(x_t)$; (6) $\Delta^2 \log(x_t)$; (7) $\Delta(x_t/x_{t-1} - 1)$. The FRED column gives instead the FRED mnemonics, while the last column provides a short description.

	TCODE	**FRED**	**Description**
1	2	FEDFUNDS	Effective Federal Funds Rate
2	2	CP3Mx	3-Month AA Financial Commercial Paper Rate
3	2	TB3MS	3-Month Treasury Bill
4	2	TB6MS	6-Month Treasury Bill
5	2	GS1	1-Year Treasury Rate
6	2	GS5	5-Year Treasury Rate
7	2	GS10	10-Year Treasury Rate
8	2	AAA	Moody's Seasoned Aaa Corporate Bond Yield
9	2	BAA	Moody's Seasoned Baa Corporate Bond Yield
10	1	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS
11	1	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS
12	1	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS
13	1	T1YFFM	1-Year Treasury C Minus FEDFUNDS
14	1	T5YFFM	5-Year Treasury C Minus FEDFUNDS
15	2	T10YFFM	10-Year Treasury Rate
16	2	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS
17	2	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS
18	1	TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies
19	1	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate
20	1	EXJPUSx	Japan / U.S. Foreign Exchange Rate
21	1	EXUSUKx	U.S. / U.K. Foreign Exchange Rate
22	1	EXCAUSx	Canada / U.S. Foreign Exchange Rate

Group 1: Interest and Exchange Rates.

	TCODE	FRED	Description
23	2	HWI	Help-Wanted Index for United States
24	2	HWIURATIO	Ratio of Help Wanted/No. Unemployed
25	5	CLF16OV	Civilian Labor Force
26	5	CE16OV	Civilian Employment
27	2	UNRATE	Civilian Unemployment Rate
28	2	UEMPMEAN	Average Duration of Unemployment (Weeks)
29	5	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks
30	5	UEMP5TO14	Civilians Unemployed for 5-14 Weeks
31	5	UEMP15OV	Civilians Unemployed - 15 Weeks & Over
32	5	UEMP15T26	Civilians Unemployed for 15-26 Weeks
33	5	UEMP27OV	Civilians Unemployed for 27 Weeks and Over
34	5	CLAIMSx	Initial Claims
35	5	PAYEMS	All Employees: Total nonfarm
36	5	USGOOD	All Employees: Goods-Producing Industries
37	5	CES1021000001	All Employees: Mining and Logging: Mining
38	5	USCONS	All Employees: Construction
39	5	MANEMP	All Employees: Manufacturing
40	5	DMANEMP	All Employees: Durable goods
41	5	NDMANEMP	All Employees: Nondurable goods
42	5	SRVPRD	All Employees: Service-Providing Industries
43	5	USTPU	All Employees: Trade, Transportation Utilities
44	5	USWTRADE	All Employees: Wholesale Trade
45	5	USTRADE	All Employees: Retail Trade
46	5	USFIRE	All Employees: Financial Activities
47	5	USGOVT	All Employees: Government
48	1	CES0600000007	Avg Weekly Hours : Goods-Producing
49	2	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing
50	1	AWHMAN	Avg Weekly Hours : Manufacturing
51	6	CES0600000008	Avg Hourly Earnings : Goods-Producing
52	6	CES2000000008	Avg Hourly Earnings : Construction
53	6	CES3000000008	Avg Hourly Earnings : Manufacturing

Group 2: Labor Market.

	TCODE	FRED	Description
54	4	HOUST	Housing Starts: Total New Privately Owned
55	4	HOUSTNE	Housing Starts, Northeast
56	4	HOUSTMW	Housing Starts, Midwest
57	4	HOUSTS	Housing Starts, South
58	4	HOUSTW	Housing Starts, West
59	4	PERMIT	New Private Housing Permits (SAAR)
60	4	PERMITNE	New Private Housing Permits, Northeast (SAAR)
61	4	PERMITMW	New Private Housing Permits, Midwest (SAAR)
62	4	PERMITS	New Private Housing Permits, South (SAAR)
63	4	PERMITW	New Private Housing Permits, West (SAAR)

Group 3: Housing.

	TCODE	FRED	Description
64	5	DPCERA3M086SBEA	Real personal consumption expenditures
65	5	CMRMTSPLx	Real Manu. and Trade Industries Sales
66	5	RETAILx	Retail and Food Services Sales
67	5	ACOGNO	New Orders for Consumer Goods
68	5	AMDMNOx	New Orders for Consumer Goods
69	5	ANDENOx	New Orders for Nondefense Capital Goods
70	5	AMDMUOx	Unfilled Orders for Durable Goods
71	5	BUSINVx	Total Business Inventories
72	2	ISRATIOx	Total Business: Inventories to Sales Ratio
73	2	UMCSENTx	Consumer Sentiment Index

Group 4: Consumption, Orders, and Inventories.

	TCODE	FRED	Description
74	6	M1SL	M1 Money Stock
75	6	M2SL	M2 Money Stock
76	5	M2REAL	Real M2 Money Stock
77	5	MZMSL	MZM Money Stock
78	6	AMBSL	St. Louis Adjusted Monetary Base
79	6	TOTRESNS	Total Reserves of Depository Institutions
80	7	NONBORRES	Reserves Of Depository Institutions
81	6	BUSLOANS	Commercial and Industrial Loans
82	6	REALLN	Real Estate Loans at All Commercial Banks
83	6	NONREVSL	Total Nonrevolving Credit
84	2	CONSPI	Nonrevolving consumer credit to Personal Income
85	6	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding
86	6	DTCTHFNM	Total Consumer Loans and Leases Outstanding
87	6	INVEST	Securities in Bank Credit at All Commercial Banks

Group 5: Money and Credit.

	TCODE	FRED	Description
88	5	S&P 500	S&P's Common Stock Price Index: Composite
89	5	S&P: Indust	S&P's Common Stock Price Index: Industrials
90	2	S&P: Div. Yield	S&P's Composite Common Stock: Dividend Yield
91	5	S&P: PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio
92	1	VXOCLSx	CBOE Volatility Index

Group 6: Stock Market.

	TCODE	FRED	Description
93	5	RPI	Real Personal Income
94	5	W875RX1	Real Personal Income Excluding Transfer Receipts
95	5	INDPRO	Industrial Production (IP) Index
96	5	IPFPNSS	IP: Final Products and Nonindustrial Supplies
97	5	IPFINAL	IP: Final Products
98	5	IPCONGD	IP: Consumer Goods
99	5	IPDCONGD	IP: Durable Consumer Goods
100	5	IPNCONGD	IP: Nondurable Consumer Goods
101	5	IPBUSEQ	IP: Business Equipment
102	5	IPMAT	IP: Materials
103	5	IPDMAT	IP: Durable Materials
104	5	IPNMAT	IP: Nondurable Materials
105	5	IPMANSICS	IP: Manufacturing (SIC)
106	5	IPB51222s	IP: Residential Utilities
107	5	IPFUELS	IP: Fuels
108	2	CUMFNS	Capacity Utilization: Manufacturing

Group 7: Output and Income.

	TCODE	FRED	Description
109	6	WPSFD49207	PPI: Finished Goods
110	6	WPSFD49502	PPI: Finished Consumer Goods
111	6	WPSID61	PPI: Intermediate Materials
112	6	WPSID62	PPI: Crude Materials
113	6	OILPRICEx	Crude Oil, spliced WTI and Cushing
114	6	PPICMM	PPI: Metals and metal products:
115	1	CPIAUCSL	CPI: All Items
116	6	CPIAPPSL	CPI: Apparel
117	6	CPITRNSL	CPI: Transportation
118	6	CPIMEDSL	CPI: Medical Care
119	6	CUSR0000SAC	CPI: Commodities
120	6	CUSR0000SAD	CPI: Durables
121	6	CUSR0000SAS	CPI: Services
122	6	CPIULFSL	CPI: All Items Less Food
123	6	CUSR0000SA0L2	CPI: All items less shelter
124	6	CUSR0000SA0L5	CPI: All items less medical care
125	6	PCEPI	Personal Cons. Exp.: Chain Index
126	6	DDURRG3M086SBEA	Personal Cons. Exp.: Durable goods
127	6	DNDGRG3M086SBEA	Personal Cons. Exp.: Nondurable goods
128	6	DSERRG3M086SBEA	Personal Cons. Exp.: Services

Group 8: Prices.

A.2 Weights of Individual Regressors in Constructing the Factors

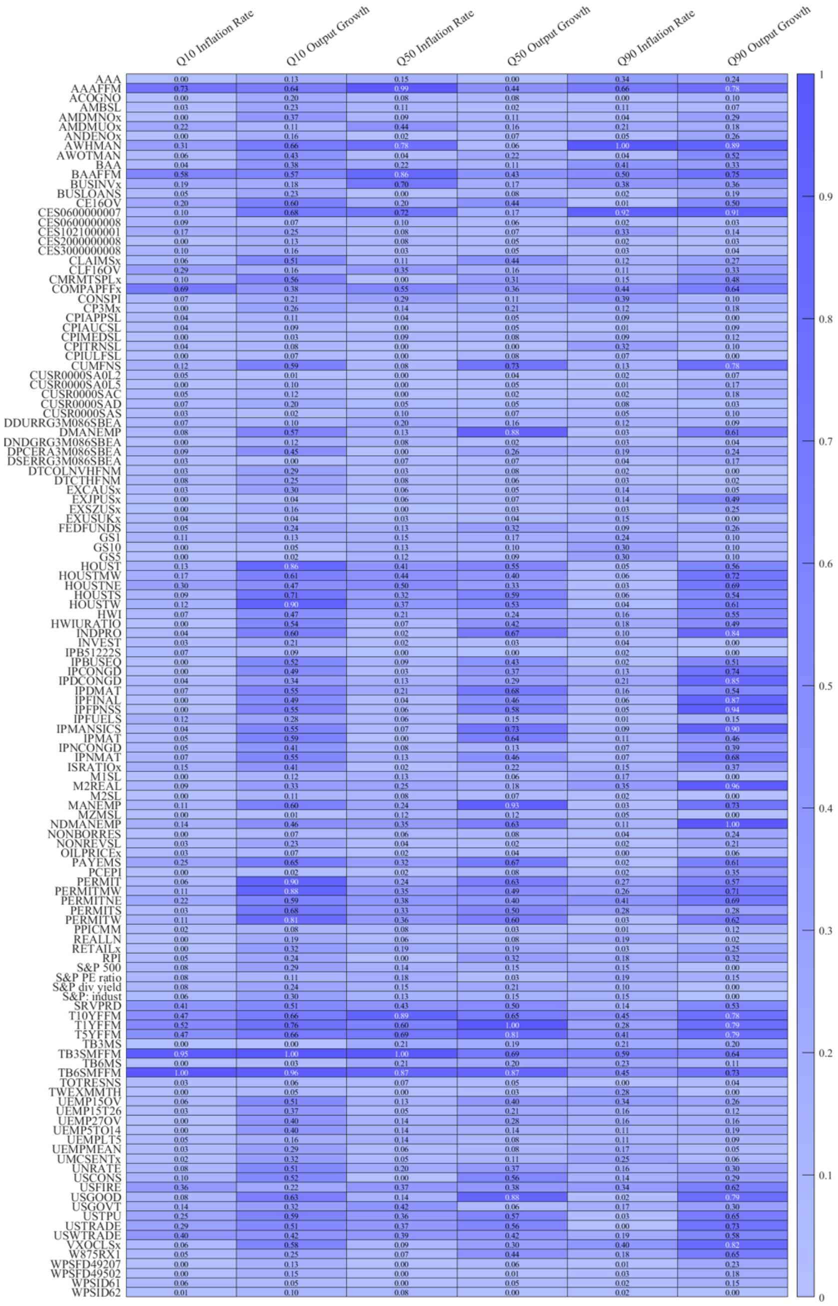

Figure A.1: Weights of Individual Regressors in Constructing the Factors $\hat{f}_t$.

Notes: Weights are derived by using the absolute value of first-stage slope estimates $\hat{\phi}_i$. To facilitate comparison, they are then rescaled to fall between 0 (smallest contributor) and 1 (largest contributor).

Output Growth

	Quantile 10*th*	Quantile 50*th*	Quantile 90*th*
1	TB3SMFFM (+2.15)	T1YFFM (+1.18)	NDMANEMP (+1.22)
2	TB6SMFFM (+2.07)	MANEMP (+1.10)	M2REAL (+1.17)
3	HOUSTW (+1.94)	DMANEMP (+1.05)	IPFPNSS (+1.15)
4	PERMIT (+1.93)	USGOOD (+1.04)	CES0600000007 (-1.12)
5	PERMITMW (+1.89)	TB6SMFFM (+1.03)	IPMANSICS (+1.11)
6	HOUST (+1.85)	T5YFFM (+0.96)	AWHMAN (-1.09)
7	PERMITW (+1.74)	CUMFNS (+0.87)	IPFINAL (+1.07)
8	T1YFFM (+1.63)	IPMANSICS (+0.86)	IPDCONGD (+1.05)
9	HOUSTS (+1.53)	TB3SMFFM (+0.81)	INDPRO (+1.02)
10	PERMITS (+1.46)	IPDMAT (+0.81)	VXOCLSx (-1.00)
11	CES0600000007 (+1.46)	INDPRO (+0.79)	T1YFFM (+0.97)
12	AWHMAN (+1.43)	PAYEMS (+0.79)	USGOOD (+0.97)
13	T5YFFM (+1.43)	T10YFFM (+0.77)	T5YFFM (+0.97)
14	T10YFFM (+1.41)	IPMAT (+0.65)	T10YFFM (+0.96)
15	PAYEMS (+1.40)	PERMIT (+0.75)	CUMFNS (+0.96)

Table A.1: Top Fifteen Contributors.

Notes: The coefficients in brackets are the slope estimates $\hat{\phi}_i$ obtained from the first-stage of PQR.

Inflation Rate

	Quantile 10*th*	Quantile 50*th*	Quantile 90*th*
1	TB6SMFFM (-1.19)	TB3SMFFM (-1.52)	AWHMAN (-2.60)
2	TB3SMFFM (-1.14)	AAAFFM (-1.50)	CES0600000007 (-2.39)
3	AAAFFM (-0.88)	T10YFFM (-1.36)	AAAFFM (-1.72)
4	COMPAPFFx (-0.82)	TB6SMFFM (-1.33)	TB3SMFFM (-1.52)
5	BAAFFM (-0.69)	BAAFFM (-1.30)	BAAFFM (-1.29)
6	T1YFFM (-0.62)	AWHMAN (-1.18)	T10YFFM (-1.17)
7	T10YFFM (-0.56)	CES0600000007 (-1.10)	TB6SMFFM (-1.16)
8	T5YFFM (-0.56)	BUSINVx (+1.06)	COMPAPFFx (-1.14)
9	SRVPRD (+0.49)	T5YFFM (+1.05)	T5YFFM (-1.08)
10	USWTRADE (+0.47)	T1YFFM (-0.91)	PERMITNE (-1.08)
11	USFIRE (+0.43)	COMPAPFFx (-0.83)	BAA (+1.07)
12	AWHMAN (-0.36)	HOUSTNE (+0.76)	VXOCLSx (+1.04)
13	HOUSTNE (+0.35)	HOUSTMW (+0.67)	CONSPI (-1.01)
14	CLF16OV (+0.35)	AMDMUOx (+0.66)	BUSINVx (+1.00)
15	USTRADE (+0.34)	SRVPRD (+0.65)	M2REAL (-0.90)

Table A.2: Top Fifteen Contributors.

Notes: The coefficients in brackets are the slope estimates $\hat{\phi}_i$ obtained from the first-stage of PQR.

A.3 Estimated Factors

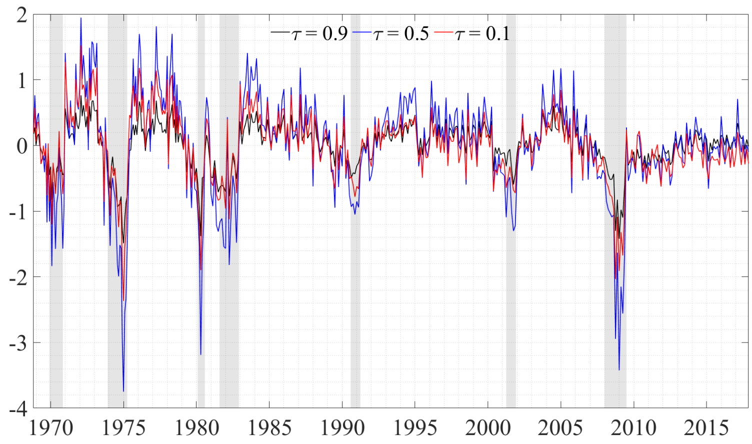

Figure A.2: Estimated Factors for Greenbook Forecasts for Output Growth.

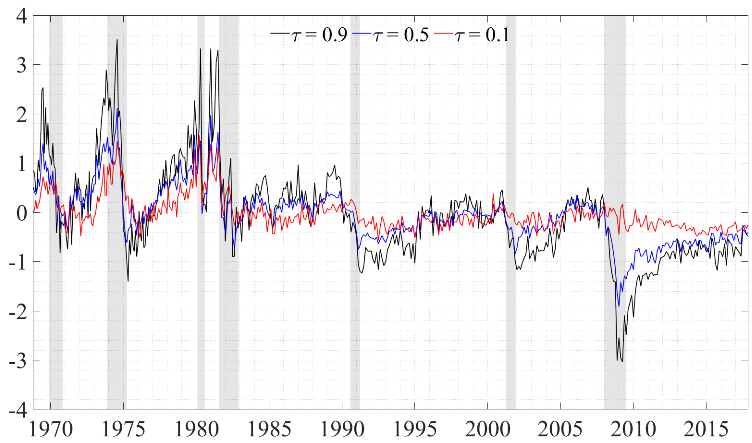

Figure A.3: Estimated Factors for Greenbook Forecasts for Inflation Rate.

A.4 Upside and Downside Uncertainty for Greenbook Forecasts

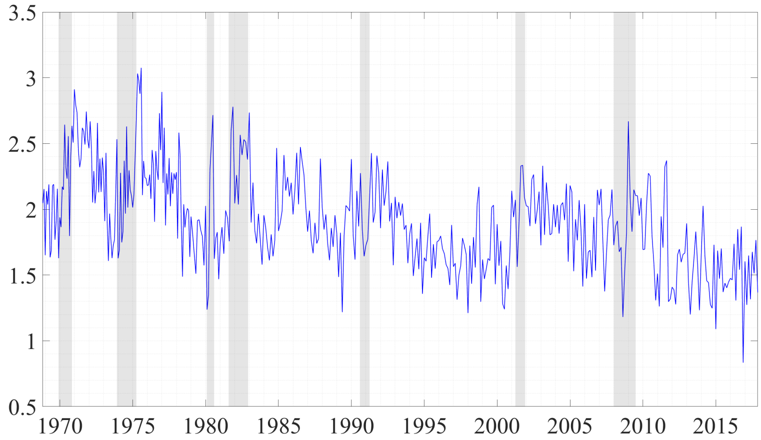

Figure A.4: Upside Uncertainty for Output Growth.

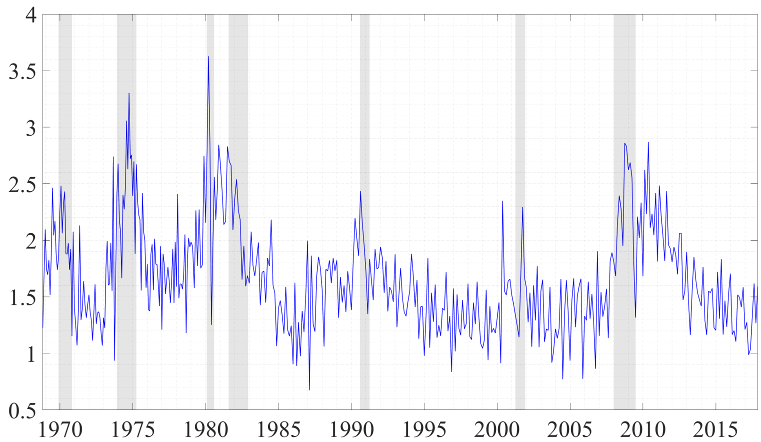

Figure A.5: Downside Uncertainty for Output Growth.

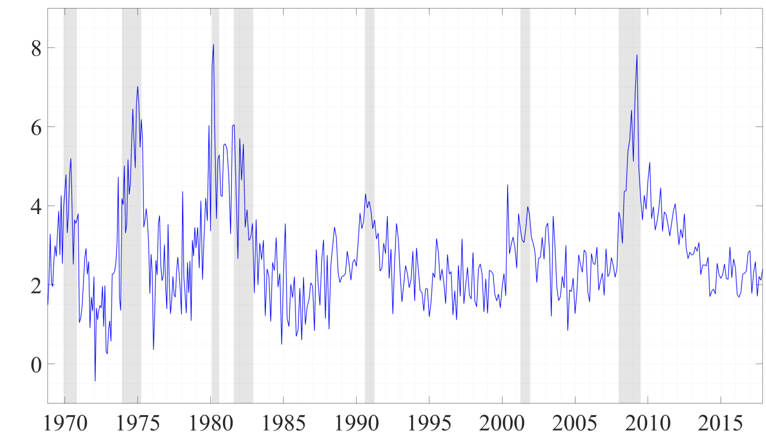

Figure A.6: Upside Uncertainty for Inflation Rate.

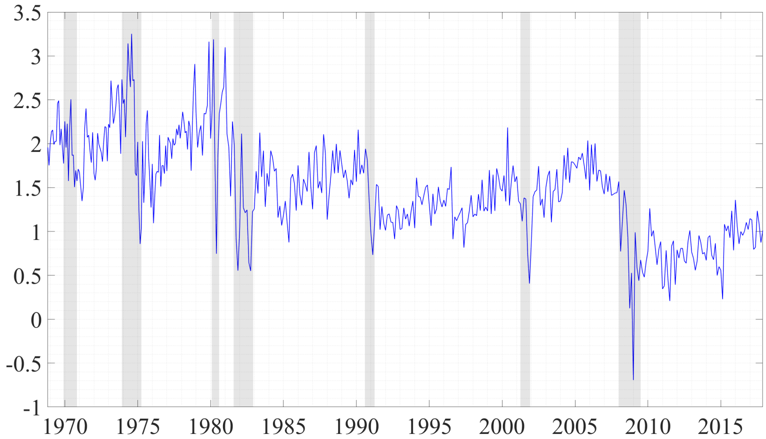

Figure A.7: Downside Uncertainty for Inflation Rate.

B Relationship with Alternative Indicators of Higher Moments

B.1 Relationship With Forecast Disagreement Among FOMC Members

In this section, I compare the indicators of uncertainty obtained from the quantile factor model with indexes of forecast disagreement among FOMC members. To run this analysis, I use the information contained in Fed's Summary of Economic Projections (SEP). From 2008 onwards, in conjunction with four FOMC meetings per year, it collects FOMC members individual forecasts about the future economic conditions that they view as the most likely to prevail.

In particular, for $i = \{gdp, \pi\}$, I compute the index of forecast disagreement D_t^i as,

$$D_t^i = F_t^{0.9,i} - F_t^{0.1,i} \tag{A.1}$$

where $F_t^{0.9,i}$ and $F_t^{0.1,i}$ are the $90th$ and $10th$ quantile of the set of individual forecasts submitted by the FOMC participants. As shown in Figure B.1, disagreement and uncertainty show similar patterns and the peak is reached in the occasion of the same FOMC meeting. Furthermore, the correlation coefficient between forecast disagreement and uncertainty is particularly high and amounts to 0.64 for output growth and to 0.61 for inflation.

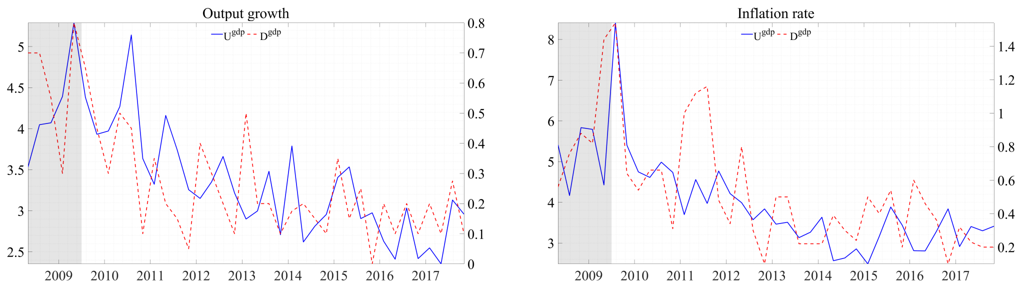

Figure B.1: Forecast Dispersion *vs* FOMC Members Disagreement.

B.2 Juardo et al's (2015) Macroeconomic Uncertainty

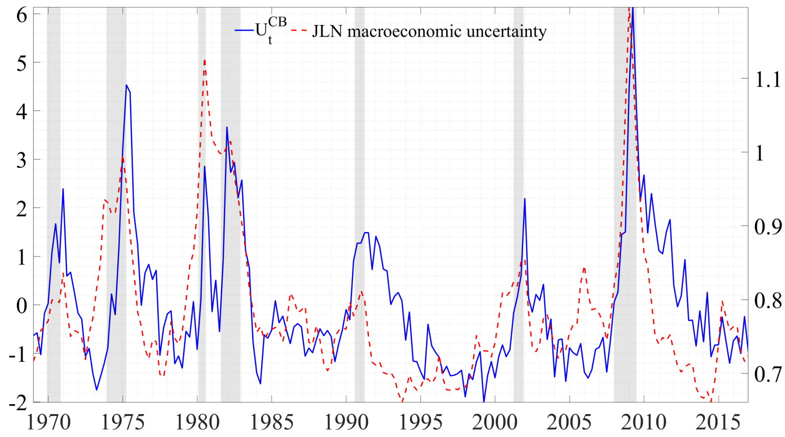

Figure B.2: U_t^{CB} *vs* JLN macroeconomic Uncertainty.

In this section, I construct an aggregate measure of Fed-based uncertainty U_t^{CB} by averaging across U_t^{gdp} and U_t^{π}. Below, I compare U_t^{CB} with the indicator of macroeconomic uncertainty computed by Jurado et al. (2015) (henceforth, JLN), that is an extremely popular benchmark in the uncertainty literature. Their index is derived in three steps. First, they use factor-augmented autoregressive models to obtain predictions for a large number of macroeconomic time series. Second, they employ stochastic volatility models to estimate the volatility of the unforecastable component of the future value of each variable. Finally, they construct an aggregate indicator by averaging across all the volatility measures. In order to run this comparison, I convert U_t^{CB} to quarterly frequency and derive the correlation coefficient with the one-quarter-ahead JLN indicator. The two measures are found to display a strong positive correlation, that amounts to 0.78. This can be probably better appreciated from Figure A.1, that compares the two indexes. They both tend to spike during recessions, with peaks occurring at the beginning of the 1980s and during the Global Financial Crisis.

B.3 Iseringhausen et al's (2023) Macroeconomic Skewness

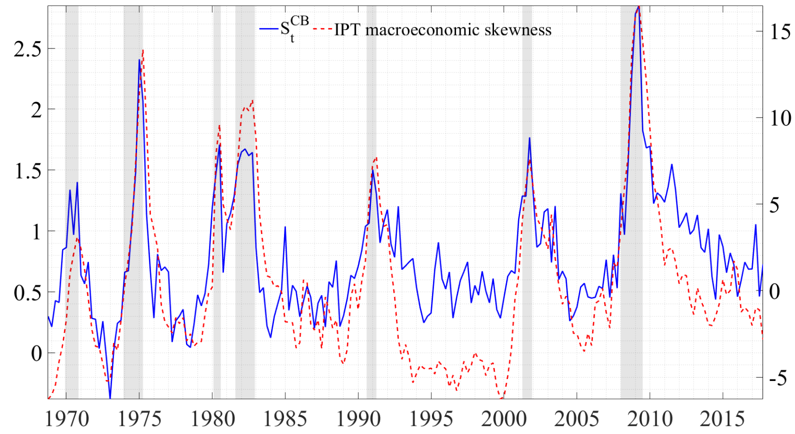

Figure B.3: S_t^{CB} *vs* IPT Macroeconomic Skewness.

In this section, I build an aggregate index of Fed-based absolute skewness S_t^{CB} by averaging across S_t^{gdp} and S_t^{π}, and I compare it with Iseringhausen et al.'s (2023) index of macroeconomic skewness. The latter is computed as the first principal component of a large number of individual measures of skewness for US macroeconomic variables, that are derived by employing the autoregressive quantile regression approach proposed by Engle and Manganelli (2004). As can be seen from Figure B.2, despite the clear methodological differences, the two indicators display a strong positive comovement, with a correlation coefficient that amounts to 0.82.

B.4 Aruoba and Drechsel's (2023) Fed Staff Sentiment

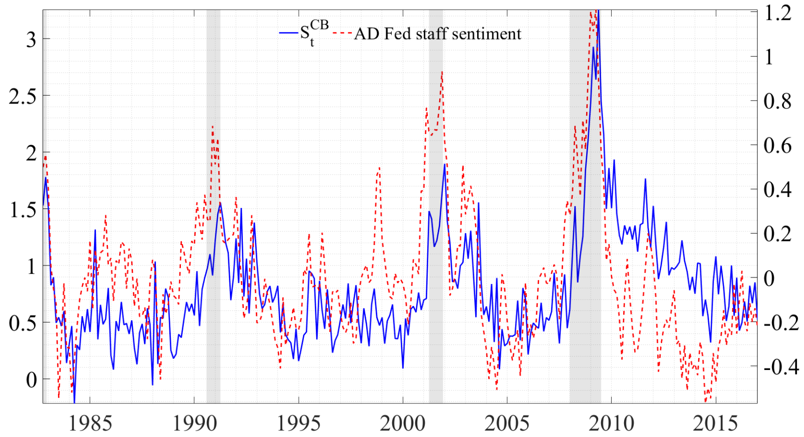

Figure B.4: U_t^{CB} *vs* AD Fed Staff Sentiment.

In this section, I compare the aggregate index of Fed-based skewness S_t^{CB} with a summary measure of Fed economists' perception of risks to the economic outlook. The latter is obtained as the first principal component of more than 250 sentiment indicators extracted using natural language processing techniques from the Greenbook documents by Aruoba and Drechsel (2023). As shown in Figure A.3, the two indexes show an extremely similar pattern, with a correlation coefficient that amounts to 0.44.

C Real-Time Analysis

This section compares the measures of uncertainty and skewness estimated on the full sample with real-time counterparts. The latter, in particular, are derived by first using the sample 1969-1990 to estimate the conditional quantiles of the Greenbook forecasts produced for the FOMC meeting held in January 1991, and by then recursively expanding the estimation window until the end of 2017. The estimated real-time conditional quantiles of Greenbook projections for output growth and inflation, for $\tau = \{0.1, 0.5, 0.9\}$, are plotted in Figure C.1.

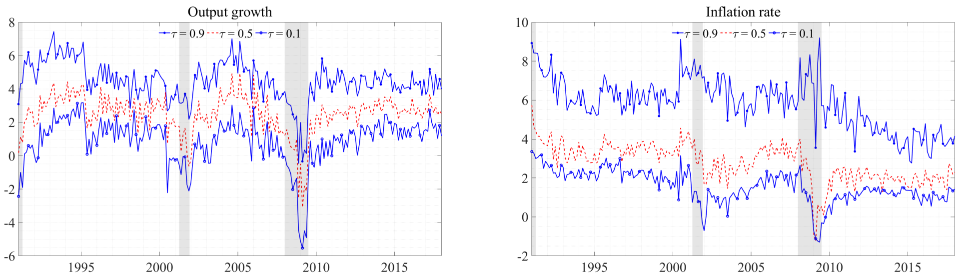

Figure C.1: Real-Time Conditional Quantiles of Greenbook Forecasts Over Time.

As shown in Figure C.2, the resulting real-time indicators of uncertainty display a strong positive comovement with those introduced in Section 4. The correlation coefficients amount in fact to 0.81 for both output growth and inflation rate. A similar finding holds for the indicators

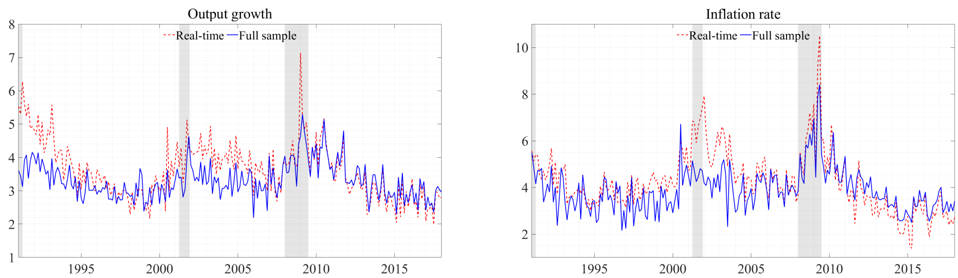

Figure C.2: Real-Time *vs* Full Sample Uncertainty for Greenbook Forecasts.

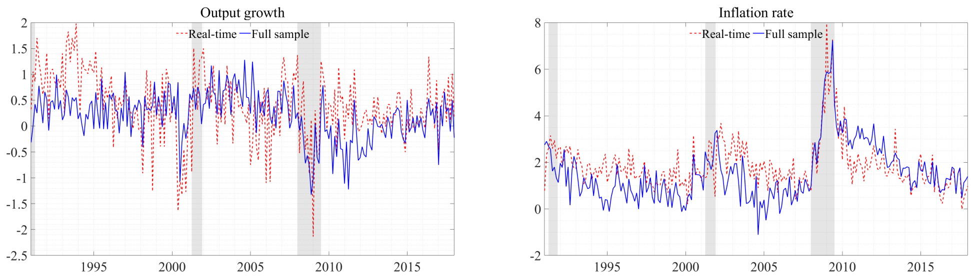

Figure C.3: Real-Time *vs* Full Sample Skewness for Greenbook Forecasts.

of skewness, that are displayed in Figure C.3. In this case, the correlation coefficients are equal to 0.82 for inflation rate and to 0.43 for output growth.

D Quantile-Based *vs* Parametric Measures of Greenbook Forecast Dispersion

This section compares the nonparametric indexes of Greenbook forecast dispersion generated by the quantile factor model with indicators obtained from a parametric model based on the one proposed by Adrian et al. (2019), that allow for time-variation in the first and second moment.

More in detail, I estimate the following conditional heteroskedasticty model at the FOMC meeting frequency,

$$y_{t,i} = \gamma_0 + \gamma_1 z_{t-1} + \sigma_{t,i}\varepsilon_{t,i} \tag{A.2}$$

$$\ln(\sigma_{t,i}) = \delta_0 + \delta_1 z_{t-1} \tag{A.3}$$

where $\varepsilon_{t,i} \sim N(0,1)$. The model is estimated by imposing a 'horseshoe' prior, that implies a belief in approximate sparsity for the model coefficients. In particular, letting $j = 1,\ldots,128$ denote the j-th regressor in McCracken and Ng's (2016) dataset, it assumes

$$(\gamma_{1,j}|\lambda_{\gamma,j},\tau_\gamma) \overset{indep}{\sim} N(0,\lambda^2_{\gamma,j}), \quad (\lambda_{\gamma,j},\tau_\gamma) \overset{iid}{\sim} \text{Cauchy}^+(0,\tau_\gamma), \quad \tau_\gamma \sim \text{Cauchy}^+(0,1)$$
$$(\delta_{1,j}|\lambda_{\delta,j},\tau_\delta) \overset{indep}{\sim} N(0,\lambda^2_{\delta,j}), \quad (\lambda_{\delta,j},\tau_\delta) \overset{iid}{\sim} \text{Cauchy}^+(0,\tau_\delta), \quad \tau_\delta \sim \text{Cauchy}^+(0,1)$$

where '$\text{Cauchy}^+(0,c)$' is the Cauchy distribution restricted to $[0,\infty]$ with location parameter 0 and scale coefficient c. Crucially, there are different scale parameters $\lambda_{\gamma,j}$ and $\lambda_{\delta,j}$ corresponding to each mean or volatility coefficient. As shown by Carvalho et al. (2010), the so-called 'signal-to-noise' ratio $\frac{1}{1+\lambda^2_{\gamma,j}}$ for the coefficient $\gamma_{1,j}$ (and similarly for $\delta_{1,j}$) has a U-shaped prior density. This implies that the posterior distribution for $\gamma_{1,j}$ and $\delta_{1,j}$ either shrinks the coefficient towards zero or hardly shrinks the coefficient at all. The outcome is thus a model with only a few selected regressors whose coefficients are not biased by the shrinkage. To sample from the posterior distribution of the conditional heteroskedasticty model, I use the automated Markov Chain Monte Carlo (MCMC) software STAN. In particular, following Plagborg-Møller et al. (2020), I run four parallel MCMC chains, starting from OLS estimates of the parameters.

Convergence is confirmed by using the $\hat{R}$ metric of Gelman and Rubin (1992) and by visual inspection of the parameter trace plot. Each chain does 5000 warm-up and 5000 further iterations. This yields a total of 20000 stored parameters. The effective sample size (once adjusted for serial correlation in the chain) is larger than 1000 in all cases.

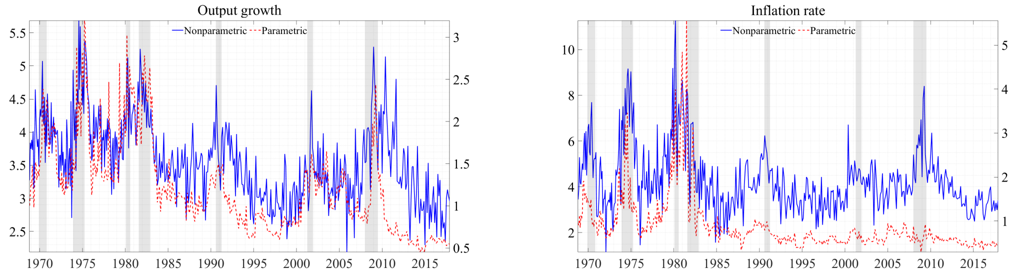

Figure D.1: Nonparametric Measures D_t^i *vs* Parametric Measures σ_t^i of Greenbook Forecast Dispersion.

In Figure D.1, I compare the estimates for $\sigma_{t,i}$, for $i = \{gdp, \pi\}$, derived from the conditional heteroskedasticity model with the indicators of Greenbook forecast dispersion derived through the quantile factor model, D_t^{gdp} and D_t^{π}. The nonparametric and the parametric measures of Greenbook forecast dispersion for output growth and inflation display, overall, a similar trend. Specifically, the correlation coefficient is equal to 0.73 and 0.71, respectively. For inflation, the visual comparison is complicated by the change in the scale of $\sigma_{t,\pi}$ that occurs starting with the Great Moderation. The latter is mainly due to a more regular dynamic of hours worked (code AWHMAN) and 5-year Treasury bond yield minus the federal funds rate (code T5YFFM). As shown in Figure D.3, they are the key drivers of $\sigma_{t,\pi}$, since their parameters, unlike the vast majority of the other ones, are not shrunken by the imposition of the horseshoe prior. Below, for completeness, I also show the posterior of volatility coefficients $\delta_{1,j}$ derived from the conditional heteroskedasticity models estimated for output growth and inflation rate Greenbook forecasts.

D.1 Output Growth

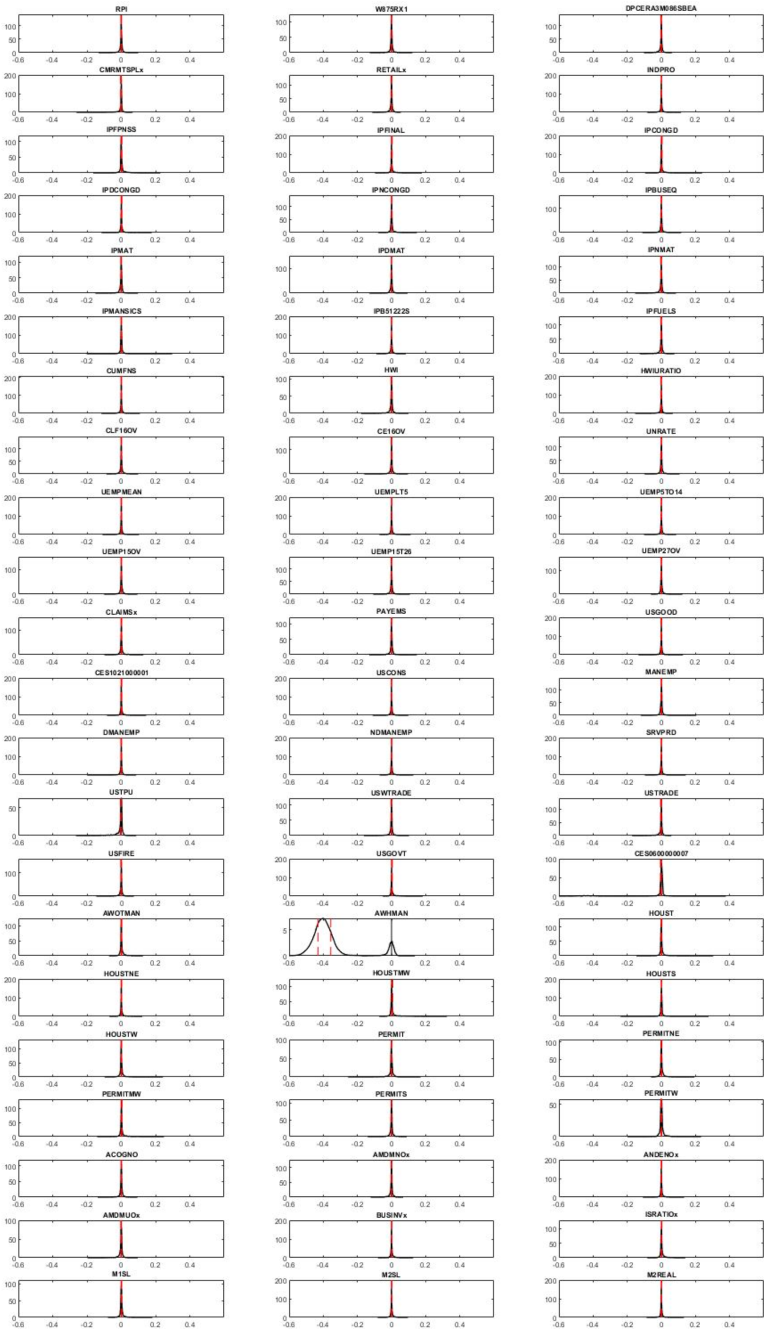

Figure D.2: Posterior of Volatility Coefficients $\delta_{1,j}$ (Part I).

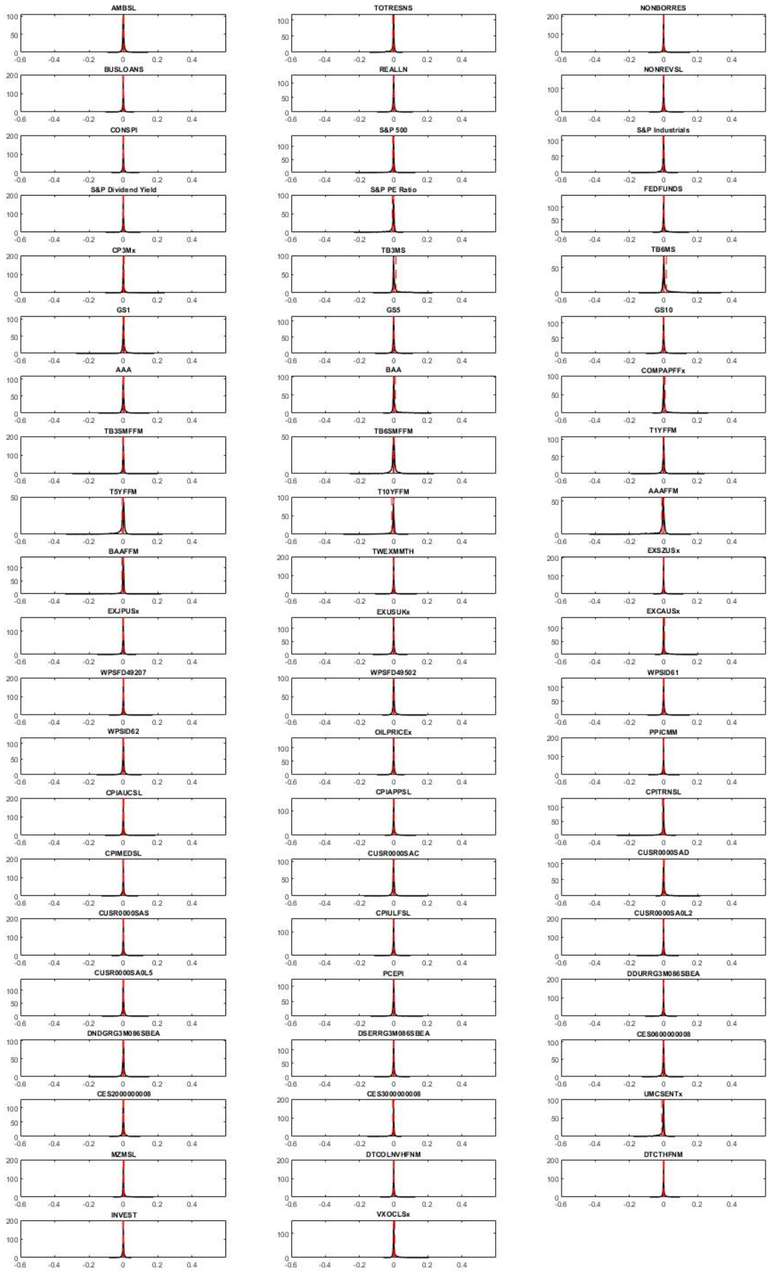

Figure D.3: Posterior of Volatility Coefficients $\delta_{1,j}$ (Part II).

D.2 Inflation Rate

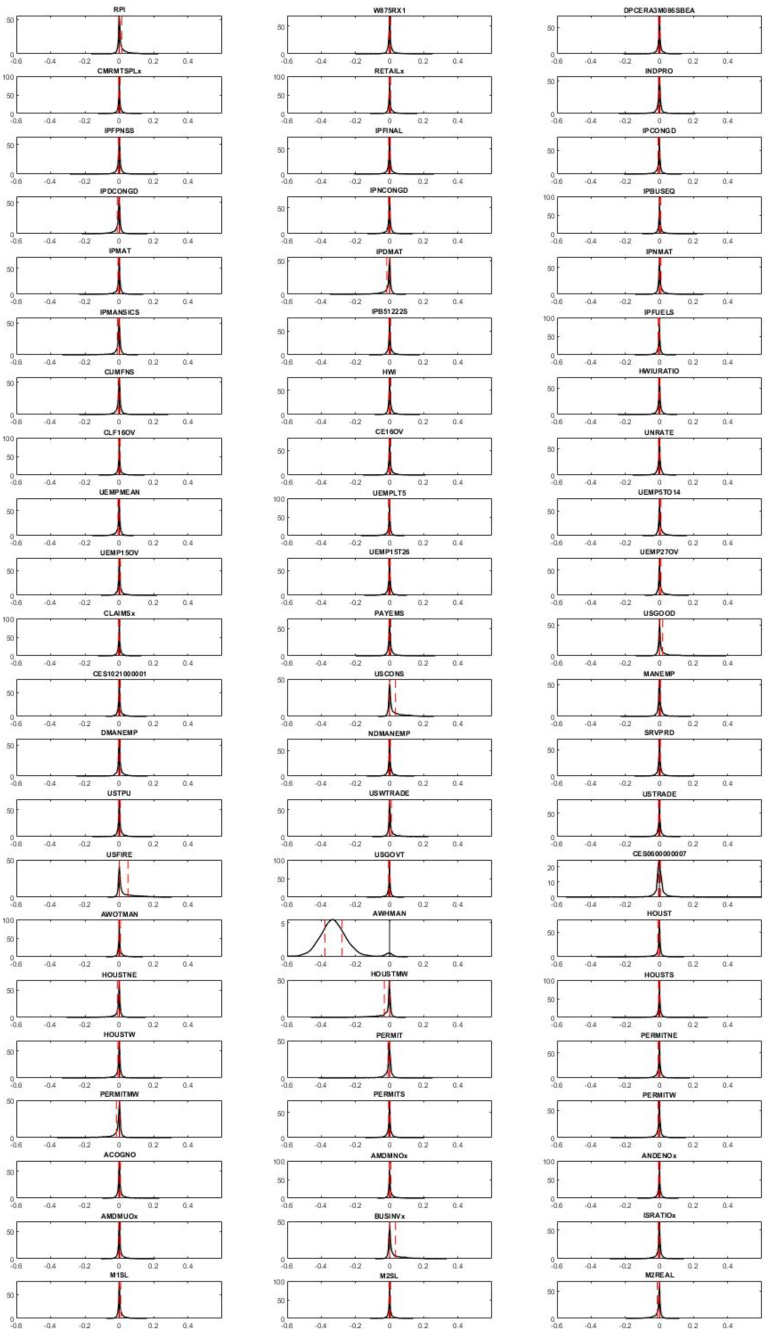

Figure D.4: Posterior of Volatility Coefficients $\delta_{1,j}$ (Part I).

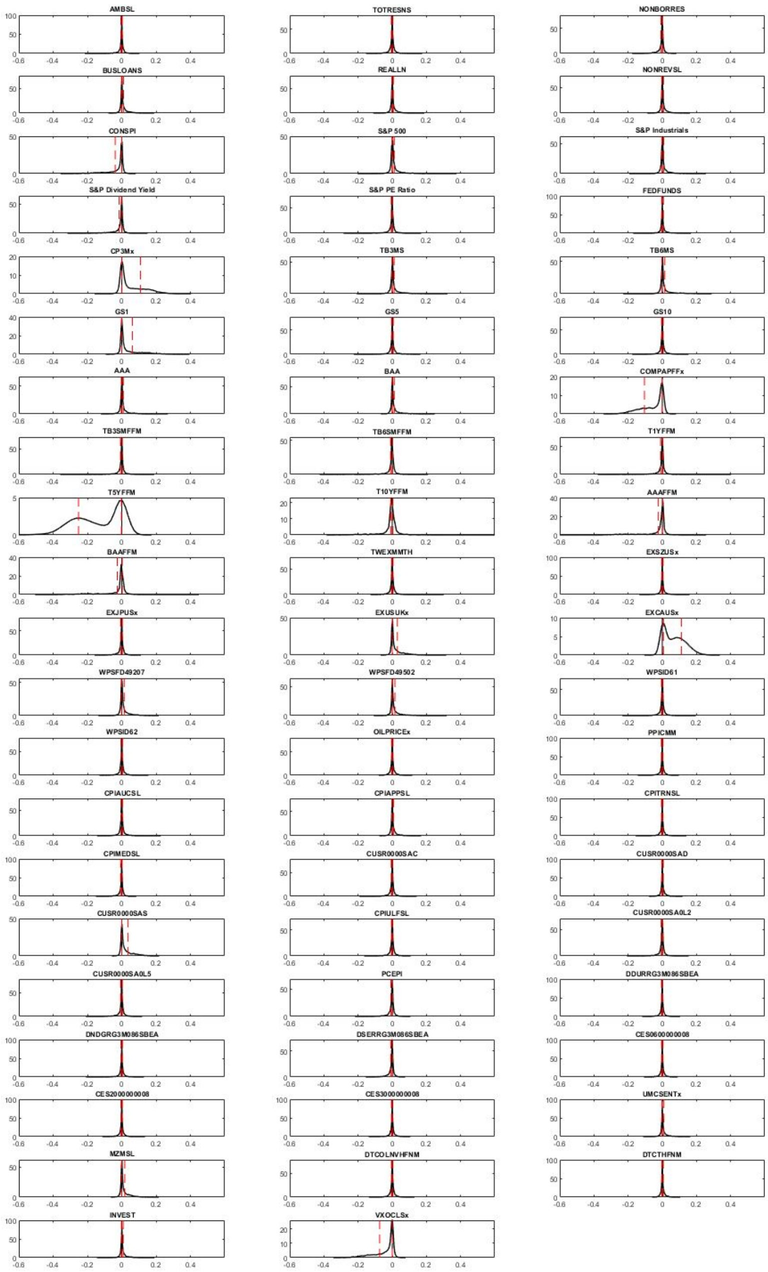

Figure D.5: Posterior of Volatility Coefficients $\delta_{1,j}$ (Part II).

E Absolute Loss Function

Under an absolute loss function, the objective function can be expressed as follows,

$$E_t L(\pi_{t+1}) = E_t |z_t - \lambda i_t + \varepsilon_{t+1}| \tag{A.4}$$

By solving the first order condition, we obtain:

$$\frac{\partial E_t L(\pi_{t+1})}{\partial i_t} = E_t \frac{\partial L(\pi_{t+1})}{\partial i_t} = E_t \frac{-\lambda (z_t - \lambda i_t + \varepsilon_{t+1})}{|z_t - \lambda i_t + \varepsilon_{t+1}|} = 0 \tag{A.5}$$

The above amounts to

$$\frac{\partial E_t L(\pi_{t+1})}{\partial i_t} = -\lambda Pr(z_t - \lambda i_t > \varepsilon_{t+1}) + \lambda Pr(z_t - \lambda i_t < \varepsilon_{t+1}) = 0 \tag{A.6}$$

This implies that $\frac{\partial E_t L(\pi_{t+1})}{\partial i_t} = 0$ if and only if $Pr(z_t - \lambda i_t > \varepsilon_{t+1}) = Pr(z_t - \lambda i_t < \varepsilon_{t+1})$. For this condition to hold, it is therefore necessary that:

$$z_t - \lambda i_t = M_t \varepsilon_{t+1} \tag{A.7}$$

where the operator M denotes the median value of the probability distribution of its argument. Hence, it follows that the optimal interest rate i_t is given by,

$$i_t = \frac{z_t}{\lambda} + \frac{M_t \varepsilon_{t+1}}{\lambda} \tag{A.8}$$

The first implication of this finding is that the principle of certainty equivalence does not hold under absolute loss functions, as first pointed out by Al-Nowaihi and Stracca (2002). Second, and more importantly, the optimal behavior of a central bank under an absolute loss function is consistent with the empirical evidence provided in Section 5. If the probability distribution of

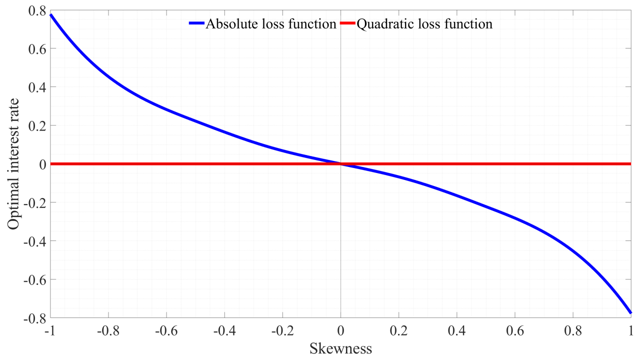

Figure E.1: Optimal Interest Rate for Different Skewness of the Distribution of ε_{t+1} Under Absolute Loss Function and Under Quadratic Loss Function.

ε_{t+1} is positively skewed, $M_t\varepsilon_{t+1}$ will be negative (given that it will be smaller than $E_t\varepsilon_{t+1} = 0$) and this will result in a more expansionary monetary policy than in the case of zero skewness (where $M_t\varepsilon_{t+1} = E_t\varepsilon_{t+1}$).

F Higher Moments and Monetary Policy

F.1 Augmenting Romer and Romer's (2004) Regression, 1983-2008

	(1) Δff	(2) Δff	(3) Δff
Constant	0.03	0.27*	0.13
	(0.07)	(0.15)	(0.31)
Pre-meeting intended funds rate	-0.05***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)
Forecasted inflation -1	0.00	0.01	0.01
	(0.02)	(0.02)	(0.02)
Forecasted inflation 0	0.04**	0.05***	0.05**
	(0.02)	(0.02)	(0.02)
Forecasted inflation +1	0.01	-0.02	-0.03
	(0.04)	(0.03)	(0.04)
Forecasted inflation +2	0.09***	0.09***	0.09**
	(0.03)	(0.03)	(0.04)
Change in inflation forecast -1	0.02	0.01	0.01
	(0.03)	(0.02)	(0.02)
Change in inflation forecast 0	-0.05*	-0.04	-0.04
	(0.03)	(0.03)	(0.03)
Change in inflation forecast +1	0.04	0.06	0.05
	(0.05)	(0.04)	(0.05)
Change in inflation forecast +2	-0.06	-0.05	-0.04
	(0.04)	(0.04)	(0.04)
Forecasted output growth -1	0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
Forecasted output growth 0	0.06***	0.02	0.02
	(0.01)	(0.02)	(0.02)
Forecasted output growth +1	0.03	0.01	0.00
	(0.02)	(0.02)	(0.02)
Forecasted output growth +2	0.00	0.03	0.04
	(0.02)	(0.02)	(0.02)
Revision in output growth forecast -1	0.00	0.03	0.02
	(0.02)	(0.02)	(0.02)
Revision in output growth forecast 0	0.04**	0.05***	0.05***
	(0.02)	(0.02)	(0.02)
Revision in output growth forecast +1	0.06**	0.07*	0.06*
	(0.03)	(0.03)	(0.03)
Revision in output growth forecast +2	0.04	0.01	0.01
	(0.03)	(0.03)	(0.03)
Forecasted unemployment rate 0	-0.06***	-0.03*	-0.04**
	(0.01)	(0.02)	(0.02)
Uncertainty - Inflation		0.05*	0.05*
		(0.03)	(0.03)
Uncertainty - Output growth		-0.00	0.01
		(0.04)	(0.04)
Skewness - Inflation		-0.11***	-0.11***
		(0.03)	(0.03)
Skewness - Output growth		-0.10**	-0.09*
		(0.05)	(0.05)
Lagged uncertainty - Inflation		-0.02	-0.02
		(0.03)	(0.03)
Lagged uncertainty - Output growth		-0.02	-0.02
		(0.04)	(0.04)
Lagged skewness - Inflation		-0.06*	-0.05
		(0.03)	(0.03)
Lagged skewness - Output growth		-0.12***	-0.10**
		(0.04)	(0.05)
Controls	No	No	Yes
R^2	0.56	0.62	0.64
Adjusted R^2	0.51	0.57	0.49
Number of observations	208	208	208

Table F.1: Augmenting Romer and Romer's (2004) Regression, 1983-2008.

Notes: Controls include macroeconomic, real and financial uncertainty (Jurado et al., 2015), an index of macroeconomic skewness (Iseringhausen et al., 2023) and Fed sentiment indicators for output growth and inflation rate (Aruoba and Drechsel, 2023). HAC standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

F.2 Autocorrelation of Romer and Romer's (2004) Shock vs HMR Shock

	(1) **R&R shock**	(2) **HMR shock**
Constant	0.00	0.00
	(0.01)	(0.01)
shock_{t-1}	0.15*	0.07
	(0.08)	(0.09)
shock_{t-2}	0.19**	0.14*
	(0.08)	(0.08)
shock_{t-3}	-0.12	-0.12
	(0.08)	(0.09)
shock_{t-4}	0.07	0.00
	(0.08)	(0.07)
shock_{t-5}	0.04	0.02
	(0.08)	(0.08)
shock_{t-6}	-0.02	0.03
	(0.07)	(0.08)
shock_{t-7}	-0.12	-0.18**
	(0.08)	(0.07)
shock_{t-8}	0.07	-0.02
	(0.07)	(0.07)
shock_{t-9}	0.11	0.07
	(0.07)	(0.06)
shock_{t-10}	-0.08	-0.07
	(0.08)	(0.08)
shock_{t-11}	-0.11*	-0.10
	(0.07)	(0.06)
shock_{t-12}	0.03	-0.01
	(0.07)	(0.07)
R^2	0.10	0.08
F-statistics	1.78	1.28
p-value	0.05	0.24
Observations	188	188

Table F.2: Autocorrelation in Monetary Policy Shocks.

Notes: HAC standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01. Estimation sample: 1983-2007.

F.3 SVAR With Internal Instrument

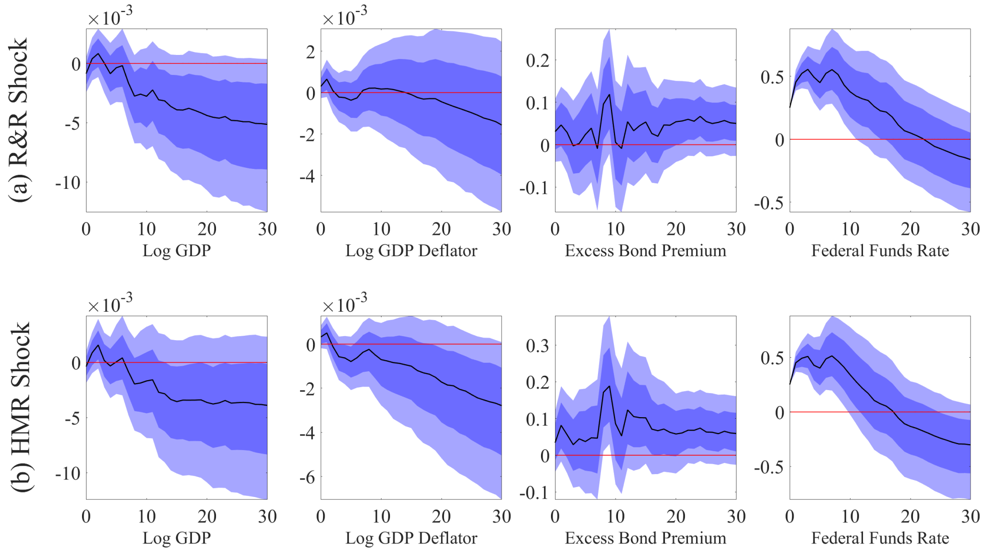

Figure F.1: Dynamic Effects of R&R Shock *vs* HMR Shock in a SVAR With Internal Instrument.

Notes: Solid lines are median estimates (computed across 2000 draws). Light and dark blue bands are 68% and 90% confidence intervals. Monetary policy shocks are normalized to induce a 25 basis points rise in ff_t.

In this section, I assess the transmission of HMR and Romer and Romer's (2004) shocks by employing them as internal instruments in a SVAR (see Plagborg-Møller and Wolf, 2021). This approach consists in ordering the instrument first in a recursively identified VAR. In addition to the monetary policy instrument, the VAR contains: the log of the real GDP gdp_t, the log of the GDP deflator pi_t, the excess bond premium ebp_t, and the federal funds rate ff_t. In particular, the VAR is estimated over the period 1983-2007 by imposing diffuse priors and including 12 lags of the endogenous variables as well as an intercept. As displayed in Figure F.2, the impulse response functions are very similar to those obtained under local projections.

F.4 Autocorrelation in High-Frequency Monetary Policy Instruments

	(1) No higher moments controls	(2) With higher moments controls
Constant	-0.00	-0.00
	(0.00)	(0.00)
MPI_{t-1}^{FF4}	-0.25***	-0.18**
	(0.07)	(0.07)
MPI_{t-2}^{FF4}	-0.18**	-0.16**
	(0.07)	(0.07)
MPI_{t-3}^{FF4}	0.01	-0.02
	(0.09)	(0.08)
MPI_{t-4}^{FF4}	0.04	0.03
	(0.11)	(0.12)
MPI_{t-5}^{FF4}	0.11	0.13
	(0.09)	(0.10)
MPI_{t-6}^{FF4}	-0.08	-0.05
	(0.07)	(0.06)
MPI_{t-7}^{FF4}	-0.02	-0.01
	(0.09)	(0.08)
MPI_{t-8}^{FF4}	-0.18	-0.16
	(0.12)	(0.08)
MPI_{t-9}^{FF4}	-0.15**	-0.12
	(0.07)	(0.06)
MPI_{t-10}^{FF4}	-0.08	-0.08
	(0.09)	(0.09)
MPI_{t-11}^{FF4}	-0.10	-0.09
	(0.06)	(0.06)
MPI_{t-12}^{FF4}	0.08	0.06
	(0.09)	(0.09)
R^2	0.13	0.10
F-statistics	1.62	1.13
p-value	0.09	0.34
Observations	140	140

Table F.4: Autocorrelation in MPI_t^{FF4}.

Notes: HAC standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01. Estimation sample: 1990-2008.

G Higher Moments and the Transmission of Monetary Policy and Central Bank Information Shocks

In Figure G.1 and G.2, I show how controlling for higher moments of Greebook forecasts affect the transmission of monetary policy and central bank information shocks identified employing

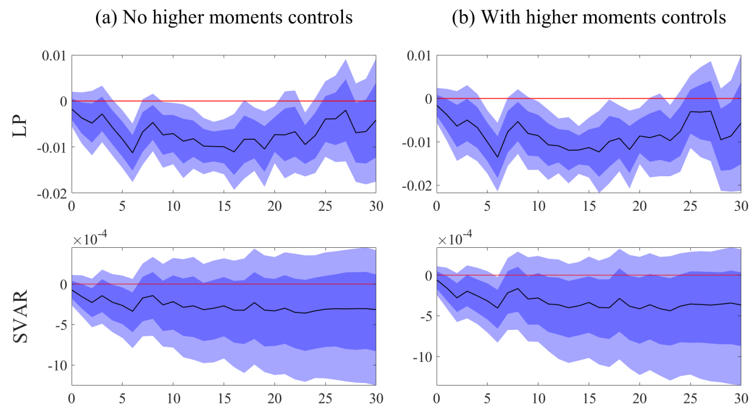

Figure G.1: Response of GDP Deflator to a Contractionary Monetary Policy Shock.

Notes: The local projections are estimated by using the same specification as in equation (14). The SVAR is instead based on the vector of variables $y_t = [gdp_t, pi_t, ebp_t, ff_t]$. In particular, the VAR is estimated by imposing Jeffreys (flat) priors and including 12 lags of the endogenous variables as well as an intercept. In both cases, the period taken into account goes from 1990 to 2007.

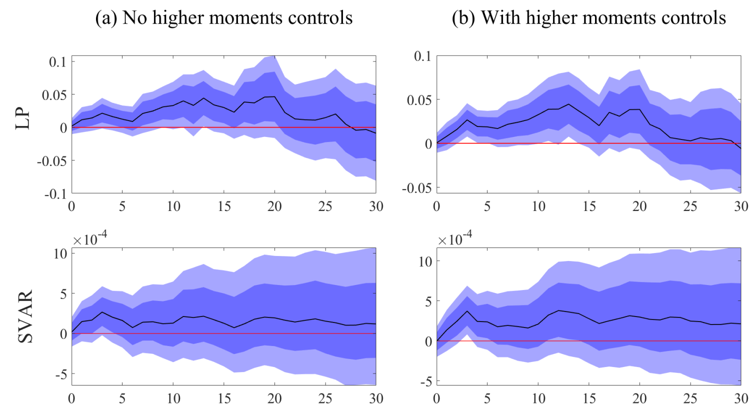

Figure G.2: Response of GDP Deflator to a Positive Central Bank Information Shock.

Notes: The local projections are estimated by using the same specification as in equation (14). The SVAR is instead based on the vector of variables $y_t = [gdp_t, pi_t, ebp_t, ff_t]$. In particular, the VAR is estimated by imposing Jeffreys (flat) priors and including 12 lags of the endogenous variables as well as an intercept. In both cases, the period taken into account goes from 1990 to 2007.

high-frequency surprises. In particular, I focus on the effects on prices. The first row refers to the case where MPI_t^{FF4} and $INFO_t^{FF4}$ are used in a local projections setting, while the second to the case when they are used as internal instrument in a SVAR that consists of the same variables introduced in Appendix F. While there are no significant differences for the transmission of monetary policy shocks, the effects on prices of central bank information shocks are larger when higher moments are taken into account. As suggested by the results in Figure G.2, this seems to be true regardless of the methodology used to compute the impulse responses.