Monetary Policy Decisions and Higher Moments of Federal Reserve Forecasts*

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January, 2023

Abstract

This paper investigates whether the monetary policy decisions taken by the Federal Open Market Committee might be explained by higher moments of Federal Reserve forecasts. In particular, I use quantile factor models to characterize the distribution of Greenbook forecasts and derive measures of dispersion and skewness. The latter, importantly, is found to be a crucial driver of changes in the federal funds rate. This result suggests that considering point predictions only is not enough to capture the endogenous component of monetary policy, thus leading to important implications for the identification of monetary policy shocks. Specifically, I show that controlling for higher moments allows to identify monetary shocks that display a lower degree of autocorrelation and induce theoretically consistent effects on output and prices.

Keywords: Monetary policy shocks, Quantile regressions, Factor models.
JEL Codes: E52; C51

*I am deeply indebted to Alessio Volpicella and Anastasios Karantounias for invaluable guidance and support. I also thank Valentina Corradi, Ricardo Nunes, Kjetil Storesletten and participants at the University of Surrey Macro PhD Workshop.

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1 Introduction and Related Literature

The analysis of the dynamic effects of monetary policy is one of the major challenges in empirical macroeconomics. The greatest difficulty arises from the intrinsic nature of monetary policy changes, that largely represent the central bank's endogenous response to information about future economic developments. The presence of such anticipatory movements complicates the identification of monetary policy shocks. In order to address this issue, Romer and Romer (2004) suggest to regress the changes in the intended funds rate on the Federal Reserve's internal forecasts for inflation, output and unemployment. These projections, available in the Greenbook, are prepared by the Federal Reserve staff before each Federal Open Market Committee (FOMC) meeting and play a crucial role in policy deliberations. The residuals of this regression are claimed to be purged of any endogenous movement and are thus taken as measures of monetary policy shocks.

This paper investigates whether controlling for the conditional mean of Greenbook forecasts is enough to purge monetary policy decisions of their endogenous component. In particular, I assess if FOMC decisions may also be informed by higher-order moments of conditional forecast distributions. For this purpose, I use quantile factor models to characterize the conditional probability distributions of Greenbook projections and to then compute indexes of dispersion and skewness. Finally, I employ them to estimate an augmented version of Romer and Romer's (2004) baseline regression and to recover a novel measure of monetary policy shocks.

The main result of this work is that higher-order moments of Federal Reserve internal forecasts, particularly skewness, are crucial decision-making features. This finding has important implications for the identification of monetary policy shocks. If we only control for the point estimates contained in the Greenbook, a non-negligible share of changes in the intended federal funds rate may be erroneously considered as exogenous. This might lead to a misidentification of monetary policy shocks and of their dynamic causal effects. I show that this is indeed the case by analyzing the transmission of US monetary policy shocks over the period 1983-2007. When the monetary policy shock is identified through the same regression as Romer and Romer (2004), monetary contractions are found to have puzzling effects on real activity and prices. On the other hand, when Romer and Romer's (2004) baseline regression is augmented with uncertainty and skewness measures, the resulting monetary policy shock turns out to have conventional effects on the economy.

Over the last few years, a growing literature has attempted to estimate the forecast distribution underlying point predictions. For instance, Reifschneider and Tulip (2019) derive uncertainty around consensus forecasts from the FOMC Summary of Economic Projections by employing the distribution of historical forecast errors. This approach has the drawback of not including any additional information available at the time the forecasts were released and implicitly assumes that uncertainty around forecasts is not predictable. Thus, their methodology might end up providing only a partial assessment of uncertainty, as stressed by Adams et al. (2021). The latter, by adopting the quantile regression methodology pioneered by Adrian et al. (2019), build risks around Survey of Professional Forecasters (SPF) median forecasts and find that financial information has a crucial role in shaping the conditional distribution of SPF projections. In particular, they only condition on the National Financial Conditions Index (NFCI), computed by the Federal Reserve Bank of Chicago.

The conditional distributions of the projections produced by professional forecasters or central banks, however, may be affected by several variables. These institutions have in fact access to a large amount of information that might inform their forecasts and it is not trivial to select the relevant variables. For this reason, I suggest to condition on the set of macroeconomic and financial series collected by McCracken and Ng (2016) in their large US monthly dataset. Specifically, I exploit this information by employing the partial quantile regression (PQR) methodology of Giglio et al. (2016). The latter is a valuable dimension reduction tool for conditional quantile factor models. Specifically, it condenses the cross section of predictors according to their quantile covariation with the forecast target. Then, the PQR estimates a consistent quantile forecast by defining a linear combination that weights predictors according to their predictive ability. The advantages of this approach have been recently stressed by Carriero et al. (2022), that find it to be the best-performing method to execute data reduction in a quantile regression setting. By adopting it, I estimate the conditional quantile function of Greenbook forecasts for output growth, inflation, unemployment and industrial production. I then employ them to define indexes of uncertainty and skewness for each of the four variables, as well as aggregate measures of macroeconomic and real uncertainty.

This paper is also inevitably related to the large literature on uncertainty measures. As already mentioned, I exploit the estimated conditional quantiles of Federal Reserve forecasts to derive indicators of macroeconomic and real uncertainty. To validate these indexes, I perform a comparison with Jurado et al.'s (2015) measures, that represent the most notable available benchmark. This exercise provides encouraging results: I find in fact evidence of a strong positive correlation, that amounts to 0.78 for macroeconomic uncertainty and to 0.71 for real uncertainty. Importantly, unlike Jurado et al. (2015), my indexes hinge on central bank's forecasts and may thus be thought as policymakers-based measures of uncertainty. This relates my work to Cieslak et al. (2022), measuring policymakers' uncertainty through text analysis methods. In particular, they construct an uncertainty index based on the FOMC statements by analyzing the sentences pronounced by each member in the first round of the meeting, when the economic outlook is discussed. Specifically, they build a score for each phrase mentioning "risk" or "uncertainty" and then average across them. The policymakers' uncertainty index I propose, differently from theirs, is a purely statistical object and is therefore not affected by the inevitably arbitrary choices that are needed to derive text-based indexes.

The structure of this paper is as follows. Section 2 sets the econometric framework. Section 3 introduces the uncertainty and skewness indexes derived from the conditional distribution of Greenbook forecasts. Section 4 evaluates whether these measures might help explaining the monetary policy decisions taken by the FOMC. Section 5 presents a new measure of monetary policy shocks and investigates its dynamic effects on output and prices. Section 6 draws conclusions. Finally, further information about the data is provided in the Appendix.

2 The Econometric Framework

This section first introduces standard quantile regression and then describes the partial quantile regression method proposed by Giglio et al. (2016). The latter is a dimension reduction technique for quantile factor models that I will use in Section 3 to characterize the conditional probability distribution of Federal Reserve internal forecasts.

2.1 Quantile Regression

Let y_{t+h} and $\mathcal{I}_t$ be, respectively, the target variable and the information set at time t. The τ-th quantile of y_{t+h} conditional on $\mathcal{I}_t$ is its inverse conditional probability distribution function, denoted by

$$Q_{y_{t+h}|\mathcal{I}_t}(\tau|\mathcal{I}_t) = F^{-1}_{y_{t+h}|\mathcal{I}_t}(\tau|\mathcal{I}_t) = \inf\{y : F_{y_{t+h}|\mathcal{I}_t}(y|\mathcal{I}_t) \geq \tau\} \tag{1}$$

where $F_{y_{t+h}|\mathcal{I}_t}(y|x_t)$ is the distribution function for y_{t+h} conditional on $\mathcal{I}_t$.

Now, let us define the information set $\mathcal{I}_t$ in terms of a vector of observables x_t. This allows to characterize the quantile function as the solution to an optimization problem. In particular, in a quantile regression of y_{t+h} on x_t, the regression slope β_τ is chosen to minimize the quantile weighted absolute value of errors:

$$\hat{\beta}_\tau =_{\beta_\tau \in \mathbb{R}^k} \sum_{t=1}^{T-h} \left(\tau \cdot \mathbf{1}_{(y_{t+h} \geq x_t \beta_\tau)} |y_{t+h} - x_t \beta_\tau| + (1-\tau) \cdot \mathbf{1}_{(y_{t+h} < x_t \beta_\tau)} |y_{t+h} - x_t \beta_\tau|\right) \quad (2)$$

where $\mathbf{1}_{(\cdot)}$ denotes the indicator function. The predicted value from regression (2) is the quantile of y_{t+h} conditional on x_t,

$$\hat{Q}_{y_{t+h}|x_t}(\tau|x_t) = x_t \hat{\beta}_\tau \quad (3)$$

Koenker and Bassett (1978) show that $\hat{Q}_{y_{t+h}|x_t}(\tau|x_t)$ is a consistent linear estimator of the quantile function of y_{t+h} conditional on x_t. Note that quantile regressions differ from ordinary least squares (OLS) regressions in two main respects. First, the quantile regression minimizes the sum of absolute errors, rather than the sum of squared errors. Second, it puts differential weights on the error terms depending on whether they are above or below the quantile.

Over the last few years, an increasing literature has exploited this methodology to estimate the conditional distribution of target variables. The most remarkable example is probably provided by Adrian et al. (2019), who study the conditional distribution of output growth as a function of economic and financial conditions. However, standard and uncostrained quantile regression does not seem to be most suitable tool to derive the probability distribution of Federal Reserve internal forecasts. Central banks have in fact access to an extremely large amount of information that informs their predictions. Hence, many variables may be important in characterizing the conditional distribution of Federal Reserve forecasts. Carriero et al. (2022) have recently surveyed the several shrinkage and dimension reduction techniques that might drive the quantile regression specification choice when the number of predictors is large. In this paper, in particular, I use the partial quantile regression methodology of Giglio et al. (2016), that I describe in the next paragraph. This approach, as pointed out by Carriero et al. (2022), represents an extremely useful tool to perform dimension reduction in a quantile regression setting.

2.2 Partial Quantile Regression

In general, quantile factor models are based on the assumption that the τ-th quantile of the target variable y_{t+h} conditional on the information set $\mathcal{I}_t$ is a linear function of an unobservable univariate factor f_t:

$$Q_{y_{t+h}|\mathcal{I}_t}(\tau|\mathcal{I}_t) = f_t \alpha_\tau \tag{4}$$

This formulation is identical to a standard quantile regression specification, except that f_t is latent. Following Kelly and Pruitt (2015), let us assume that the large cross section of predictors x_t follow a factor structure of the form

$$x_t = \Lambda F_t + \varepsilon_t = \phi f_t + \psi g_t + \varepsilon_t \tag{5}$$

where ε_t are idiosyncratic measurement, while the factor term F_t is assumed to consist of two components, f_t and g_t. The subset f_t collects the so-called relevant factors, that are allowed to affect the target variable y_{t+h}. On the other hand, g_t denotes the subset of irrelevant factors, that do not influence the forecast target but might instead drive the cross section of predictive information x_t.

Giglio et al. (2016) introduce two alternative dimension reduction methodologies to consistently estimate the latent factor f_t and then retrieve the conditional quantiles of y_{t+h} conditional on the large set of predictors x_t. In this paper, in particular, I use the so-called partial quantile regression (PQR) method, that extends partial least squares to the quantile regression framework. PQR summarizes the cross section of predictors according to their quantile covariation with the forecast target. Specifically, a consistent quantile factor estimate is derived as linear combination of the predictors in x_t, where the weights depend on their predictive ability. More in detail, the steps to obtain PQR estimates of the τ-th quantile of y_{t+h} conditional on the set of predictors x_t can be summarized as follows.

1. Estimate univariate τ-th quantile regressions of y_{t+h} on a constant and $x_{i,t}$ to get slope estimate $\hat{\phi}_i$.

2. Compute the cross-section covariance of $x_{i,t}$ and $\hat{\phi}_i$ for each t and average across them, with weights depending on the predictive ability of each regressor, to get the factor estimate $\hat{f}_t$.

3. Estimate a univariate τ-th quantile regression of y_{t+h} on a constant and $\hat{f}_t$ to get the final-stage quantile regression coefficient $\hat{\alpha}_\tau$.

3 Higher Moments of Greenbook Forecasts

In this section, I employ this approach to estimate the quantiles of Greenbook forecasts for output growth, unemployment rate, industrial production and inflation, conditional on the variables contained in McCracken and Ng's (2016) large dataset. I then use these estimates to derive indexes of skewness and uncertainty around central bank's forecasts.

3.1 Data

I consider one-quarter-ahead Greenbook projections for output growth, inflation rate, unemployment rate and industrial production growth. These forecasts are prepared by the staff of the Federal Reserve Board prior to each FOMC meeting and their frequency is thus not regular. The FOMC convenes in fact eight times a year from 1981 onwards, while meetings were monthly till 1978 (in 1979 and 1980 they were instead, respectively, 9 and 11). In particular, I focus on the period from November 1968 to December 2016. 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 November 1968. Let gdp, π, u and ip denote, respectively, output growth, inflation rate, unemployment rate and industrial production growth. Then, $y^i_{t,q}$, with $i = \{gdp, \pi, u, ip\}$, represents the one-quarter-ahead Greenbook forecast for variable i associated to the FOMC meeting held in month t.

The vector of conditioning variables x_t consists instead of the 127 macroeconomic and financial series collected in McCracken and Ng's (2016) large US monthly dataset. A complete description of the variables is contained in Appendix A. Specifically, to avoid exploiting information that was not available at the time the forecast was produced, I condition on the realization of the variables in the month preceding the one in which the FOMC meeting is held.

3.2 Conditional Quantiles, Uncertainty and Skewness

In this section, I use PQR to estimate the quantiles of Greenbook forecasts for output growth, inflation rate, unemployment rate and industrial production growth conditional on the 127 variables in McCracken and Ng's (2016) dataset. For the remainder of this paragraph, let $\hat{Q}_{y^i_{t,q}|x_t}(\tau|x_t)$ denote the conditional τ-th quantile estimate for the one-quarter-ahead Greenbook forecast of variable i.

In Figure 1, I show the conditional quantiles of Greenbook forecasts for the cases in which $\tau = \{0.1, 0.5, 0.9\}$. The upper and lower conditional quantiles of output growth, unemployment rate and industrial production growth seem to evolve quite symmetrically over time. On the other hand, the conditional probability distribution for inflation forecasts displays a rather asymmetric behaviour over time. The upper quantiles vary significantly, while the lower ones are relatively stable. Below, I employ the conditional quantile estimates displayed in Figure 1 to derive skewness and uncertainty measures for each of the four variables.

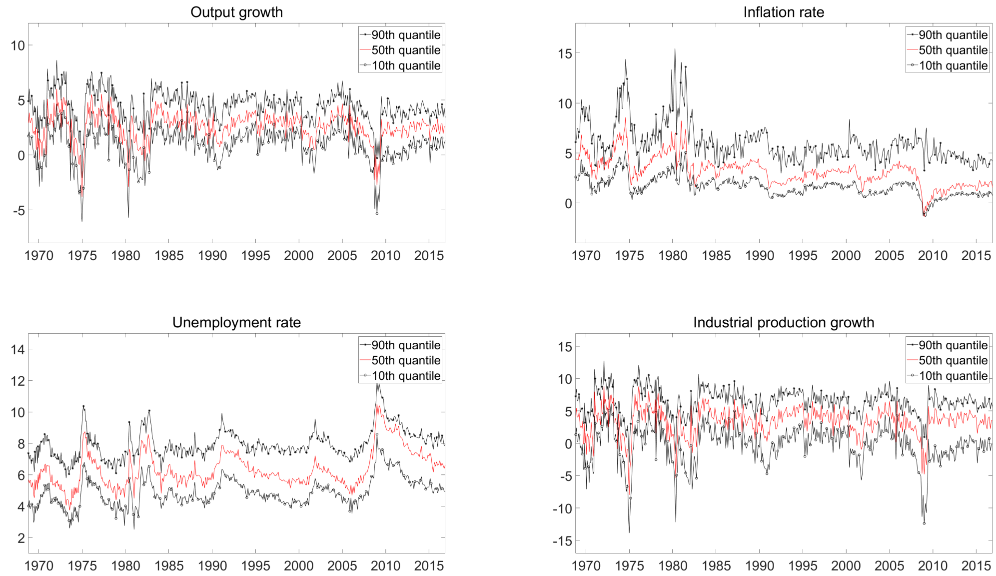

Figure 1: Conditional quantiles of Greenbook forecasts over time

For $i = \{gdp, \pi, u, ip\}$, I measure uncertainty as the dispersion of the conditional probability distribution, defined as the difference between the $90th$ and $10th$ quantile,

$$U_t^i = \hat{Q}_{y_{t+1}^i|x_t}(0.9|x_t) - \hat{Q}_{y_{t+1}^i|x_t}(0.1|x_t) \tag{6}$$

Following Forni et al. (2021), I proxy instead skewness by computing the non-normalized Kelley index (Kelley, 1947),

$$S_t^i = \left(\hat{Q}_{y_{t+1}^i|x_t}(0.9|x_t) - \hat{Q}_{y_{t+1}^i|x_t}(0.5|x_t)\right) - \left(\hat{Q}_{y_{t+1}^i|x_t}(0.5|x_t) - \hat{Q}_{y_{t+1}^i|x_t}(0.1|x_t)\right) \tag{7}$$

The resulting uncertainty and skewness indexes for output growth, inflation rate, unemployment rate and industrial production growth are reported in Appendix A.

3.3 Measuring Policymakers' Macroeconomic and Real Uncertainty

In this section, I derive policymakers-based indexes of macroeconomic and real uncertainty by aggregating the individual measures for output growth, inflation rate, unemployment rate and industrial production growth.

In particular, the policymakers' macroeconomic uncertainty index is simply defined as a weighted average of the four individual measures,

$$U_t^M = \frac{1}{4}\left(U_t^{gdp} + U_t^{\pi} + U_t^{u} + U_t^{ip}\right) \tag{8}$$

On the other hand, the policymakers' real uncertainty index is computed by averaging over the individual measures for the three real variables,

$$U_t^R = \frac{1}{3}\left(U_t^{gdp} + U_t^{u} + U_t^{ip}\right) \tag{9}$$

Below, I compare them with Jurado et al.'s (2015) indexes of macroeconomic and real uncertainty (henceforth, JLN macroeconomic and real uncertainty), that represent one of the most renowned available benchmarks. Their indicators are derived in three steps. First, they use factor-augmented autoregressive models to obtain predictions for a large number of series, that are divided into three categories (financial, macroeconomic and real variables). They then employ stochastic volatility models to estimate the volatility of the purely unforecastable component of the future value of each series. Finally, they construct aggregate indexes by averaging these measures across all the series in a certain category. To perform such a comparison, I convert U_t^M and U_t^R to quarterly frequency and compute the correlation coefficient with the corresponding one-quarter-ahead uncertainty measures derived by Jurado et al. (2015). This exercise provides encouraging results: I find in fact evidence of a strong positive correlation, that amounts to 0.78 for macroeconomic uncertainty and to 0.71 for real uncertainty. This can be probably better appreciated from Figure 2, plotting the uncertainty indexes U_t^M and U_t^R together with JLN measures of macroeconomic and real uncertainty. The Federal Reserve based

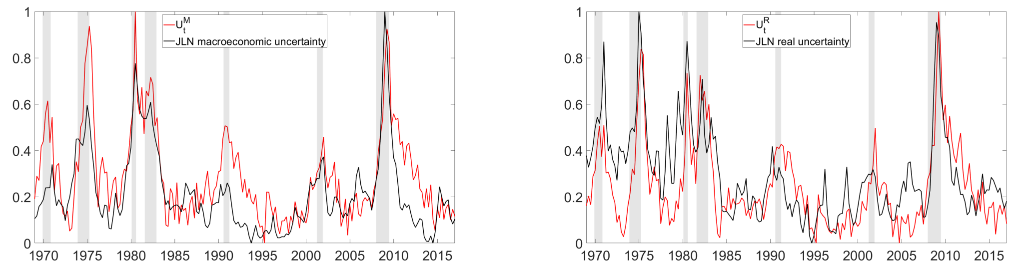

Figure 2: U_t^M and U_t^R *vs* JLN uncertainty measures
Note: Shaded bands denote US recession dates.

uncertainty indicators show a very similar pattern compared with JLN measures. In both cases, macroeconomic and real uncertainty tends to be higher during recessions, with the peak that occurs during the Global Financial Crisis.

4 Monetary Policy and Higher Moments of Greenbook Forecasts

In this section, I employ the skewness and uncertainty measures derived above to assess whether higher moments of Greenbook projections might help explaining the monetary policy decisions taken by the FOMC. The rationale behind this exercise is the following. Higher moments of Greenbook projections might influence the policy stance beyond the conditional mean forecast typically used in rule estimates. A particular point prediction may in fact be underpinned by several probability distributions and each of them could affect the policy response differently.

To help clarifying this point, let us consider an illustrative example. Figure 5 plots six density forecasts for output growth, which have all the same mean (equal to 0) but different degrees of uncertainty and skewness. Specifically, on the left panel I take into account three levels of dispersion of the forecast distribution, labelled as high, medium or low uncertainty. On the right panel, I instead consider cases in which the probability distribution underlying the zero mean point prediction is positively or negatively skewed. The key argument of this paper is that the shape of the forecast distributions, although unobservable, might inform FOMC actions. For instance, if density forecasts for output growth are affected by positive skewness (i.e. the probability mass moves towards more 'adverse' output growth realizations) the FOMC might react with a looser policy stance compared to the case in which it faces the same point prediction but with an underlying distribution that is characterized by zero (or negative) skewness.

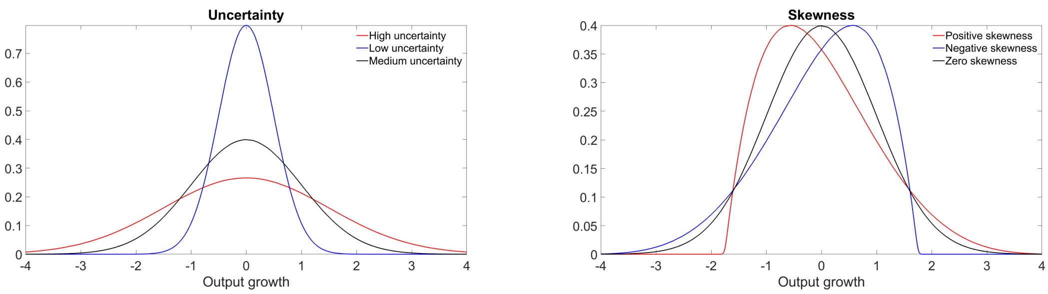

Figure 3: Monetary policy and higher moments of Greenbook forecasts: an example

To evaluate if FOMC policy actions are explained not only by the conditional mean but also by higher moments of Greenbook projections, I augment Romer and Romer's (2004) regression with uncertainty and skewness measures based on output growth and inflation forecasts. In their seminal work, Romer and Romer (2004) regress the changes in the intended funds rate deliberated in the FOMC meeting on the economic forecasts that informed those policy actions. The residuals of this regression are then considered as a measure of exogenous monetary policy shocks, since they capture the movements in the intended federal funds rate that were not triggered by information about future economic conditions. Differently from Romer and Romer (2004), who cover the period 1969-1996, my sample goes from 1983 to 2007. This choice is rather common in the literature revisiting Romer and Romer (2004), since it allows to exclude the nonborrowed reserves targeting period (from 1979 to 1983) as well as the unconventional monetary policy implemented after the Global Financial Crisis (see, for instance, Ramey, 2016).

4.1 Augmenting Romer and Romer's (2004) Regression

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

$$\begin{aligned}\Delta ff_t = \alpha + ff_t + \sum_{j=-1}^{2} \phi_j F_t^{gdp,j} + \sum_{j=-1}^{2} \theta_j F_t^{\pi,j} + \beta_0 F_t^{u,0} + \\ \sum_{j=-1}^{2} \gamma_j [F_t^{gdp,j} - F_{t-1}^{gdp,j}] + \sum_{j=-1}^{2} \vartheta_j [F_t^{\pi,j} - F_{t-1}^{\pi,j}] + \varepsilon_d^m \end{aligned} \quad (10)$$

where Δff_t denotes the change in the intended federal funds rate decided in the FOMC meeting that was held in month t; ff_t is the level of the intended federal funds rate into force before the FOMC meeting occurred; $F_t^{i,j}$, for $i = \{gdp, \pi\}$, is the Greenbook forecast 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 (10), that is denoted by ε_d^m, is then claimed to be purged of any endogenous or anticipatory movement and are thus taken as measures of monetary policy shocks. The key idea behind Romer and Romer's (2004) methodology is that Federal Reserve internal forecasts reflect all the information that is relevant for determining the monetary policy stance. From their perspective, regressing the change in the intended funds rate on the Greenbook projections is therefore enough to remove the anticipatory component of monetary policy. In this section, I question this view and verify whether FOMC monetary policy decisions might also be informed by higher moments of Federal Reserve internal forecasts. For this purpose, I enlarge the regression in (10) by including the uncertainty and skewness measures derived for output growth and inflation rate Greenbook forecasts.

In Table 1, I display the outcome of this analysis. As a benchmark, the first column reports the results obtained under Romer and Romer's (2004) baseline regression. The R^2 amounts to 0.49 and thus suggests that a large share of the change 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 is worth noting that the R^2 obtained by Romer and Romer (2004) for the sample 1969-1996 is significantly smaller and amounts to 0.29. This result is not surprising, since I am excluding periods in which (10) does not provide a good approximation of the FOMC decision-making process, because of an explicit nonborrowed reserves targeting (1979-1983) or due to other factors affecting the FOMC monetary policy actions (*e.g.* political pressures during the 1970s). In the second column, I show the results obtained when (10) is augmented with the skewness and uncertainty indicators derived for output growth and inflation. While uncertainty measures are not found to explain the movements in the intended federal funds rate, both the skewness coefficients are large and statistically different from zero. Moreover, the sign is negative and therefore consistent with the argument outlined in the previous subsection. An increase in skewness moves the forecast probability mass moves towards the left (i.e. more adverse output growth realizations or milder inflation) and triggers therefore a looser policy response. In the last column, I extend the previous specification by also including a lag of the two skewness measures, whose coefficients are statistically significant and, in line with the above economic intuition, have a negative sign. In the next section, I will consider the residuals from this third specification as a measure of monetary policy shocks and I will evaluate their dynamic effects on output and prices.

To sum up, this analysis suggests that not controlling for higher order moments of Greenbook forecasts may lead to misidentification of monetary policy shocks. Skewness measures, in particular, explain a non-negligible share of changes in the intended funds

	(1) Δff	(2) Δff	(3) Δff
Constant	0.07	0.03	0.14
	(0.06)	(0.13)	(0.13)
Pre-meeting intended funds rate	-0.06***	-0.05***	-0.06***
	(0.01)	(0.01)	(0.01)
Forecasted inflation -1	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)
Forecasted inflation 0	0.06***	0.05***	0.05***
	(0.02)	(0.02)	(0.02)
Forecasted inflation +1	0.03	0.02	0.01
	(0.04)	(0.04)	(0.04)
Forecasted inflation +2	0.03	0.03	0.04
	(0.04)	(0.04)	(0.04)
Change in inflation forecast -1	0.01	0.01	0.02
	(0.03)	(0.03)	(0.03)
Change in inflation forecast 0	-0.07**	-0.07**	-0.07**
	(0.03)	(0.03)	(0.03)
Change in inflation forecast +1	0.01	0.02	0.03
	(0.05)	(0.05)	(0.05)
Change in inflation forecast +2	0.01	0.02	0.02
	(0.06)	(0.06)	(0.06)
Forecasted output growth -1	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Forecasted output growth 0	0.06***	0.04***	0.03**
	(0.01)	(0.02)	(0.02)
Forecasted output growth +1	0.02	0.01	0.02
	(0.02)	(0.02)	(0.02)
Forecasted output growth +2	-0.02	-0.00	0.01
	(0.02)	(0.02)	(0.02)
Revision in output growth forecast -1	0.01	0.02	0.03
	(0.02)	(0.02)	0.14
Revision in output growth forecast 0	0.04*	0.04**	0.05**
	(0.02)	(0.02)	(0.02)
Revision in output growth forecast +1	0.03	0.04	0.04
	(0.03)	(0.03)	(0.03)
Revision in output growth forecast +2	0.04	0.04	0.02
	(0.03)	(0.03)	(0.03)
Forecasted unemployment rate 0	-0.05***	-0.04***	-0.03**
	(0.01)	(0.02)	(0.02)
Skewness - Inflation		-0.10***	-0.08**
		(0.03)	(0.03)
Skewness - Output growth		-0.10*	-0.10**
		(0.05)	(0.05)
Uncertainty - Inflation		0.03	0.03
		(0.03)	(0.03)
Uncertainty - Output growth		0.01	0.01
		(0.04)	(0.04)
Lagged skewness - Inflation			-0.08***
			(0.02)
Lagged skewness - Output growth			-0.09*
			(0.04)
R^2	0.49	0.52	0.55
Adjusted R^2	0.44	0.46	0.49
Number of observations	200	200	199

Table 1: Augmenting Romer and Romer's (2004) regression

rate. At the same time, the R^2 is quite far from one and indicates therefore that Federal Reserve decisions were partially taken for reasons unrelated to anticipations of output growth and inflation or to their higher moments.

5 Measuring Monetary Policy Shocks

This section studies the properties of the monetary policy shocks obtained when Romer and Romer's (2004) regression is enriched with higher moments of Greenbook forecasts. Specifically, I will take as a reference the residuals of the third specification in Table 1, that I define as higher moments robust (HMR) shock.

5.1 Variance and Autocorrelation

In Figure 4, I compare the HMR shock with the measure obtained by using Romer and Romer's (2004) approach. Despite a graphical inspection does not suggest the presence of significant differences between the two series, a couple of remarks are required.

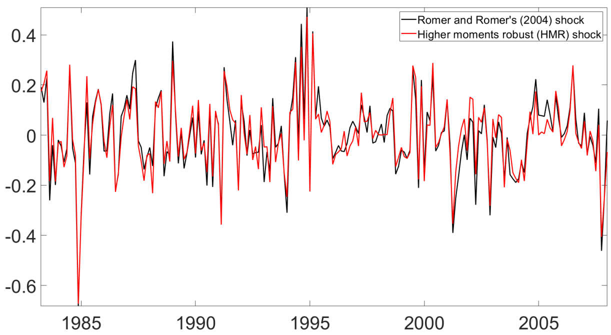

Figure 4: Romer and Romer's (2004) shock *vs* higher moments robust (HMR) shock

First, the HMR shock shows a lower variance (equal to 0.021) compared to Romer and Romer's (2004) series (that amounts to 0.024). When uncertainty and, especially, skewness measures are included in regression (10), a larger share of the changes in the intended federal funds rate is in fact endogenously explained. As a result, the volatility of the residuals is smaller.

Furthermore, the HMR shock shows a smaller degree of autocorrelation (and thus predictability) than Romer and Romer's (2004) series. Serial correlation is clearly not a desirable characteristic since a valid measure of monetary policy shocks should capture only unanticipated movements in the funds rate. To test for autocorrelation, similarly to Miranda-Agrippino and Ricco (2021), I regress HMR and Romer and Romer's (2004) shocks on their first six lags. As can be seen from Table 2, the autocorrelation structure

	(1) **R&R Shock**	**(2)** **HMR Shock**
Constant	-0.00	-0.00
	(0.01)	(0.01)
$shock_{t-1}$	0.16*	0.08
	(0.09)	(0.08)
$shock_{t-2}$	0.16*	0.13
	(0.10)	(0.09)
$shock_{t-3}$	-0.12	-0.13
	(0.09)	(0.09)
$shock_{t-4}$	0.12	0.06
	(0.08)	(0.07)
$shock_{t-5}$	0.01	-0.00
	(0.07)	(0.07)
$shock_{t-6}$	-0.05	0.00
	(0.07)	(0.08)
R^2	0.07	0.04
F-statistics	2.41	1.27
p-value	0.03	0.27
Observations	194	193

Table 2: Autocorrelation in Monetary Policy Shocks
Note: Standard errors are compute with the Newey-West heteroskedasticity and autocorrelation (HAC) robust method.

is significantly weaker when uncertainty and skewness indexes are included in the regression. This is an important result, since it shows that the serial correlation of Romer and Romer's (2004) series may be induced by the omission of higher moments of Greenbook forecasts. Hence, the analysis so far performed hinted that Romer and Romer's (2004) shocks might not be the best option to assess the transmission of US monetary policy.

In the next section, I will therefore evaluate whether using the HMR shock might lead to different implications regarding the effects of monetary policy on output and prices.

5.2 Transmission of US Monetary Policy Shocks

In this section, I use local projections (Jordà, 2005) to characterize the dynamic causal effects of US monetary policy shocks over the period 1983-2007.

Specifically, I estimate the following regression at the monthly frequency:

$$y_{t+h} = \gamma^{(h)} + \sum_{l=1}^{2} \alpha_l^{(h)} y_{t-l} + \sum_{j=0}^{5} \beta_j^{(h)} \varepsilon_{t-j}^m + u_{t+h} \tag{11}$$

where $h = 0, \ldots, 24$, ε_t^m is the monetary policy shock and $y_t' = [gdp_t \;\; pi_t]$, with gdp_t and π_t denoting, respectively, the log of real GDP and of the GDP deflator. The estimated coefficient $\hat{\beta}_0^{(h)}$ is the impulse response of the variable of interest at time $t+h$ to ε_t^m. Specifically, I compare the cases in which ε_t^m is selected as the HMR shock or the Romer and Romer's (2004) shock. By doing so, I can therefore assess whether controlling for higher moments of Grenbook forecasts might lead to different conclusions about the transmission of US monetary policy.

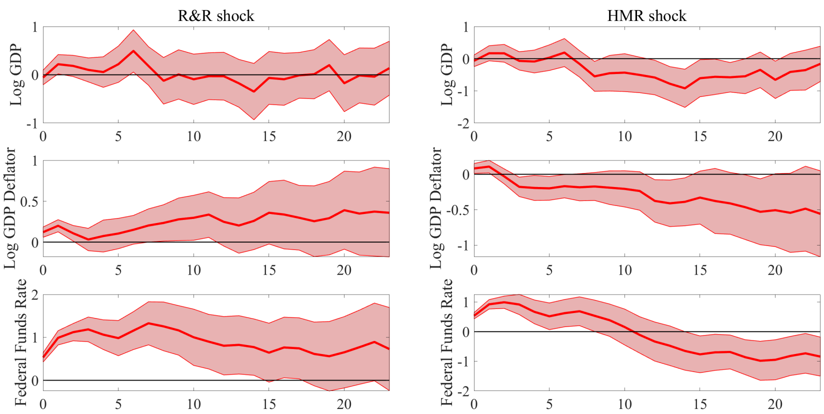

Figure 5: Dynamic effects of R&R shock *vs* HMR shock
Note: solid line is the response calculated by local projections. The shaded bands are the 68% confidence level error bands for the individual coefficients of the local projections response.

As displayed in Figure 5, Romer and Romer's (2004) shock generates quite puzzling effects. The response of output is in fact not statistically significant at any horizon while prices show a positive reaction in the very short-run. The transmission of HMR shocks is instead more easily reconcilable with theoretical predictions. The effects on real GDP are in fact found to be negative in the short to medium run. Furthermore, there is no evidence of price puzzle, with the GDP deflator that experiences a negative response. Controlling for uncertainty and skewness of Greenbook forecasts, in other words, seems to be important to recover monetary policy shocks that have standard effects on output and prices over the period 1983-2007.

6 Conclusion

This paper employs quantile factor models to characterize the probability distributions of Greenbook forecasts for output growth, inflation rate, unemployment rate and industrial production. The estimated conditional quantiles are then used to derive individual measures of skewness and uncertainty as well as aggregate indicators of macroeconomic and real uncertainty. Importantly, the latter display a substantial correlation with the indexes proposed by Jurado et al. (2015).

These measures are then used to assess whether higher moments of Federal Reserve internal forecasts may help explaining the US monetary policy stance. In particular, I find that skewness is a crucial decision-making feature that affects the FOMC monetary policy decisions beyond the point forecasts typically used in rule estimates (e.g. Romer and Romer, 2004). This result has crucial implications. Without controlling for higher moments, non-negligible shares of changes in the intended funds rate might erroneously be considered as exogenous and the dynamic effects of monetary policy shocks may thus be misidentified. I show that this is indeed the case by evaluating the transmission of US monetary policy over the period 1983-2007. When monetary policy shocks are recovered through Romer and Romer's (2004) baseline regression, US monetary contractions are found to have rather puzzling effects on real activity and prices. On the contrary, when it is augmented with uncertainty and skewness indicators, the resulting monetary policy shocks display a lower degree of autocorrelation and are found out to have conventional effects on the economy.

References

Adams, P. A., Adrian, T., Boyarchenko, N., and Giannone, D. (2021). Forecasting Macroeconomic Risks. *International Journal of Forecasting*, 37(3):1173–1191.

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable Growth. *American Economic Review*, 109(4):1263–1289.

Carriero, A., Marcellino, M., and Clark, T. E. (2022). Specification Choices in Quantile Regression for Empirical Macroeconomics. *FRB of Cleveland Working Paper*.

Cieslak, A., Hansen, S., McMahon, M., and Xiao, S. (2022). Policymakers' Uncertainty. *Working Paper*.

Forni, M., Gambetti, L., and Sala, L. (2021). Downside and Upside Uncertainty Shocks. *CEPR Discussion Paper*, No. DP15881.

Giglio, S., Kelly, B., and Pruitt, S. (2016). Systemic Risk and the Macroeconomy: An Empirical Evaluation. *Journal of Financial Economics*, 119(3):457–471.

Jordà, O. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 95(1):161–182.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, 105(3):1177–1216.

Kelley, T. L. (1947). Fundamentals of Statistics. *Harvard University Press*.

Kelly, B. and Pruitt, S. (2015). The Three-Pass Regression Filter: A New Approach to Forecasting Using Many Predictors. *Journal of Econometrics*, 186(2):294–316.

Koenker, R. and Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46(1):33–50.

McCracken, M. W. and Ng, S. (2016). FRED-MD: A Monthly Database for Macroeconomic Research. *Journal of Business & Economic Statistics*, 34(4):574–589.

Miranda-Agrippino, S. and Ricco, G. (2021). The Transmission of Monetary Policy Shocks. *American Economic Journal: Macroeconomics*, 13:74–107.

Ramey, V. (2016). Macroeconomic Shocks and Their Propagation. *Handbook of Macroe-*

conomics, 71-162.

Reifschneider, D. and Tulip, P. (2019). Gauging the Uncertainty of the Economic Outlook Using Historical Forecasting Errors: The Federal Reserve's Approach. *International Journal of Forecasting*, 35:1564–1582.

Romer, C. D. and Romer, D. H. (2004). A New Measure of Monetary Shocks: Derivation and Implications. *American Economic Review*, 94(4):1055–1084.

A McCracken and Ng's (2016) US Monthly Dataset

This section provides details about the 127 macroeconomic and financial variables used in the quantile factor model. These series are taken from McCracken and Ng's (2016) US monthly dataset and may 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 column TCODE denotes 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 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	6	AMBSL	St. Louis Adjusted Monetary Base
78	6	TOTRESNS	Total Reserves of Depository Institutions
79	7	NONBORRES	Reserves Of Depository Institutions
80	6	BUSLOANS	Commercial and Industrial Loans
81	6	REALLN	Real Estate Loans at All Commercial Banks
82	6	NONREVSL	Total Nonrevolving Credit
83	2	CONSPI	Nonrevolving consumer credit to Personal Income
84	6	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding
85	6	DTCTHFNM	Total Consumer Loans and Leases Outstanding
86	6	INVEST	Securities in Bank Credit at All Commercial Banks

Group 5: Money and credit

	TCODE	FRED	Description
87	5	S&P 500	S&P's Common Stock Price Index: Composite
88	5	S&P: indust	S&P's Common Stock Price Index: Industrials
89	2	S&P div yield	S&P's Composite Common Stock: Dividend Yield
90	5	S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio
91	1	VIX	CBOE Volatility Index

Group 6: Stock market

	TCODE	FRED	Description
92	5	RPI	Real Personal Income
93	5	W875RX1	Real Personal Income Excluding Transfer Receipts
94	5	INDPRO	Industrial Production (IP) Index
95	5	IPFPNSS	IP: Final Products and Nonindustrial Supplies
96	5	IPFINAL	IP: Final Products
97	5	IPCONGD	IP: Consumer Goods
98	5	IPDCONGD	IP: Durable Consumer Goods
99	5	IPNCONGD	IP: Nondurable Consumer Goods
100	5	IPBUSEQ	IP: Business Equipment
101	5	IPMAT	IP: Materials
102	5	IPDMAT	IP: Durable Materials
103	5	IPNMAT	IP: Nondurable Materials
104	5	IPMANSICS	IP: Manufacturing (SIC)
105	5	IPB51222s	IP: Residential Utilities
106	5	IPFUELS	IP: Fuels
107	2	CUMFNS	Capacity Utilization: Manufacturing

Group 7: Output and income

	TCODE	FRED	Description
108	6	WPSFD49207	PPI: Finished Goods
109	6	WPSFD49502	PPI: Finished Consumer Goods
110	6	WPSID61	PPI: Intermediate Materials
111	6	WPSID62	PPI: Crude Materials
112	6	OILPRICEx	Crude Oil, spliced WTI and Cushing
113	6	PPICMM	PPI: Metals and metal products:
114	1	CPIAUCSL	CPI: All Items
115	6	CPIAPPSL	CPI: Apparel
116	6	CPITRNSL	CPI: Transportation
117	6	CPIMEDSL	CPI: Medical Care
118	6	CUSR0000SAC	CPI: Commodities
119	6	CUSR0000SAD	CPI: Durables
120	6	CUSR0000SAS	CPI: Services
121	6	CPIULFSL	CPI: All Items Less Food
122	6	CUSR0000SA0L2	CPI: All items less shelter
123	6	CUSR0000SA0L5	CPI: All items less medical care
124	6	PCEPI	Personal Cons. Expend.: Chain Index
125	6	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods
126	6	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods
127	6	DSERRG3M086SBEA	Personal Cons. Exp: Services

Group 8: Prices

B Uncertainty and Skewness Measures for Greenbook Forecasts

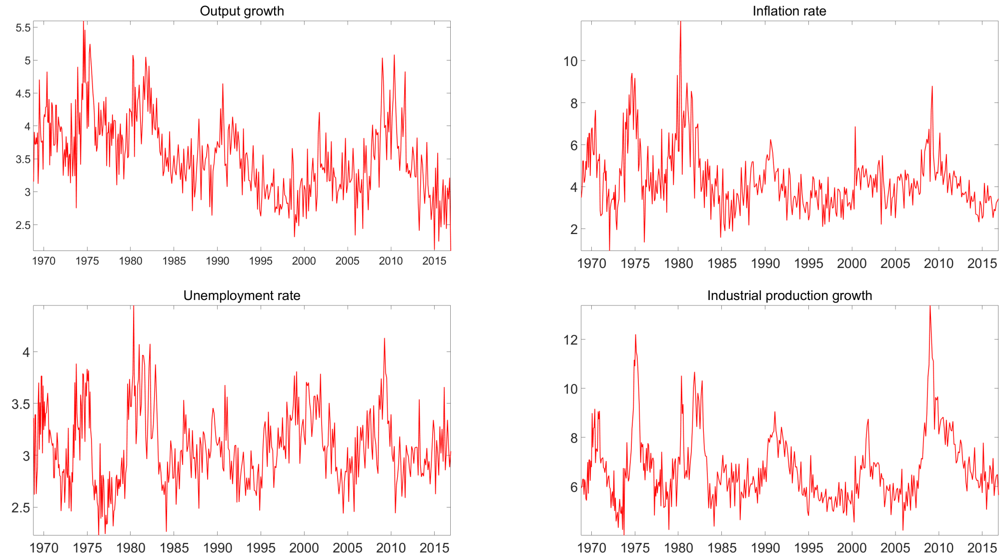

Figure A.1: Uncertainty measures

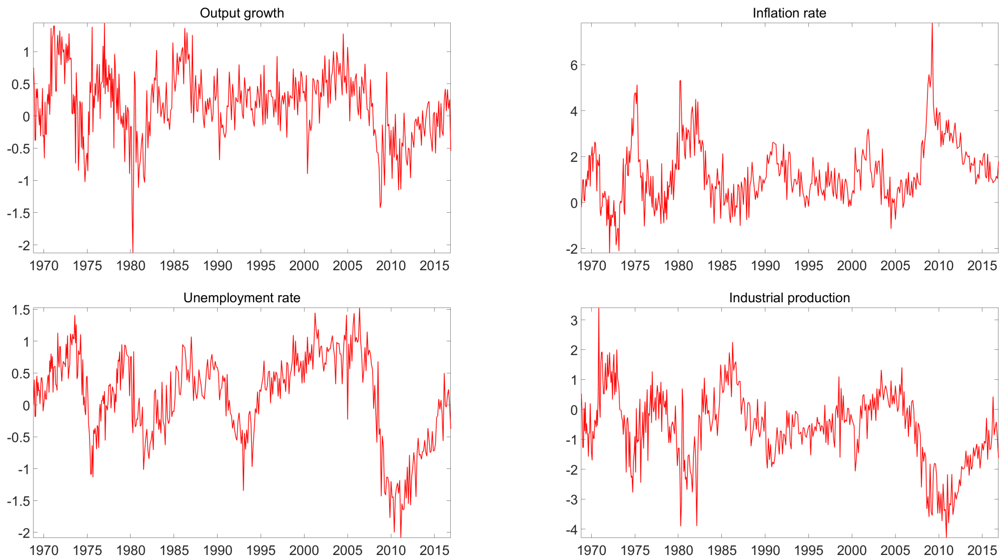

Figure A.2: Skewness measures