CESifo WORKING PAPERS

10407
2023

May 2023

Does U.S. Monetary Policy Respond to Macroeconomic Uncertainty?

Thomas Gomez, Giulia Piccillo

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 10407*

Does U.S. Monetary Policy Respond to Macroeconomic Uncertainty?

Abstract

We find that macroeconomic uncertainty plays a significant role in U.S. monetary policy. First, we construct a measure of uncertainty as felt by policymakers at the time of making their rate-setting decisions. This measure is derived from a real-time, Bayesian estimation of a small monetary VAR with time-varying parameters. We use it to calculate the probability of being in a high-uncertainty regime. Second, we estimate a monetary policy reaction function that, apart from macroeconomic uncertainty, includes Greenbook forecasts, revisions of those forecasts, and a measure of stock market volatility. Using data for the period 1969 - 2008, we find that policymakers set an interest rate that is significantly lower in a high-uncertainty regime, compared to a low-uncertainty regime.

JEL-Codes: E520, E580, E010, D810.

Keywords: monetary policy, uncertainty, real-time data, Bayesian VAR, time-varying coefficients.

Thomas Gomez
Utrecht University / The Netherlands
t.gomez@uu.nl

Giulia Piccillo
Maastricht University / The Netherlands
g.piccillo@maastrichtuniversity.nl

22 March 2023
This work was supported by the Complex Systems Fund, with special thanks to Peter Koeze.

1. Introduction

Monetary policymakers often emphasize the importance of uncertainty. Greenspan (2004), for example, notes that "uncertainty is not just a pervasive feature of the monetary policy landscape; it is the defining characteristic of that landscape" (p. 36). Uncertainty has also been proposed as an important driver of business cycles (e.g., Bloom et al., 2018; Caldara et al., 2016). The idea is that uncertainty causes cautious behaviour by consumers and firms, leading to decreasing output and increasing unemployment.[1] To counteract these effects, monetary policy should be looser in high-uncertainty regimes.[2] Uncertainty has resurfaced in the monetary policy debate in the context of the COVID-19 pandemic (e.g., Panetta, 2020).

We set out to empirically determine the response of monetary policy to macroeconomic uncertainty. Our analysis consists of two parts: (1) constructing an appropriate measure of macroeconomic uncertainty, and (2) estimating a monetary policy reaction function that includes this uncertainty measure.

An appropriate macroeconomic uncertainty measure should capture uncertainty as felt by policymakers at the time they make rate-setting decisions. In the case of the United States, this means uncertainty felt by the members of the Federal Open Market Committee (FOMC) during their meetings. We pursue this goal by incorporating three key elements.

First, we treat uncertainty as inherently subjective, and therefore take a Bayesian approach. This is in line with the description by Greenspan (2004) of the risk-management approach to monetary policy as being an application of Bayesian decision-making. Additionally, a Bayesian approach to uncertainty quantification is standard in the statistics

[1] Theoretically, the link between uncertainty and the behaviour of economic actors has been established for years. Leland (1968) shows how income uncertainty can lower consumption through precautionary savings. Batra and Ullah (1974) shows that firms decrease their output in reaction to increases in price uncertainty. The real options literature describes how (partly) irreversible consumption and investment can be postponed in uncertain times: It can be preferable to wait for more information than to make a costly mistake (e.g., Bernanke, 1983).

[2] Other reasons for monetary policy to respond to uncertainty have been proposed in the literature. Evans et al. (2016) provide an overview.

literature (e.g., Berger and Smith, 2019), and supported by evidence on human decision-making and learning (Kording, 2014; Viscusi, 1985; Yu, 2007).

Second, we base our uncertainty measure on the data that is available at the time of each FOMC meeting. This data differs from the currently available data because of data revisions, which can be substantial, especially in times of uncertainty. By using real-time data, we can measure uncertainty as perceived at the time that policymakers make rate-setting decisions. It has been known for some time that it is important to use real-time data in the analysis of monetary policy (e.g., Orphanides, 2001).

Third, we measure the uncertainty surrounding the relationships among a small set of key macroeconomic variables, namely, real output growth, inflation, and the effective federal funds rate. Our aim is to incorporate the idea formulated by Greenspan (2004, p. 37) as follows: "A critical result has been the identification of a relatively small set of key relationships that, taken together, provide a useful approximation of our economy's dynamics."

We capture these relationships in a Bayesian time-varying parameter VAR (TVP-VAR) model as in Koop and Korobilis (2013).[3] For each FOMC meeting, we estimate a Bayesian TVP-VAR on the associated real-time data. We derive the posterior density of one-quarter-ahead forecasts and compute uncertainty as its differential entropy. Entropy has previously been used to measure uncertainty (e.g., Rich and Tracy, 2010). Additionally, we check whether the uncertainty felt by policymakers, and its influence on the interest rate, might be better captured in terms of low- and high-uncertainty regimes than as a linear response. A small change in the uncertainty measure might lead to a shift in regimes and have a large interest rate effect. To take this into account, we also compute the probability of being in a high-uncertainty regime for every meeting.

In the second part of this paper, we investigate how macroeconomic uncertainty affects

[3]Their approach uses a forgetting factor, which allows for the model's coefficients to change over time. Furthermore, it is computationally efficient, which is useful because we have to recalculate the uncertainty measure (i.e., repeat the TVP-VAR estimation) for each FOMC meeting. Bayesian VARs are standard forecasting tools with a long history in macroeconometrics (e.g., Litterman, 1986). Forgetting factor approaches go as far back as the 1960s (Koop and Korobilis, 2013).

monetary policy decisions by the FED. We begin by estimating an extended version of the monetary policy reaction function used by Romer and Romer (2004). They combine quantitative and narrative sources to identify the intended change to the federal funds rate surrounding each FOMC meeting, and use this as dependent variable in their reaction function. As explanatory variables, they include Greenbook forecasts for output growth, inflation, and the unemployment rate at various horizons. They also include revisions of those forecasts compared to the previous meeting. We augment this reaction function with our macroeconomic uncertainty measure, and we also add the VXO measure of stock market volatility as a proxy for financial uncertainty.

Following Romer and Romer (2004), we estimate the reaction function meeting by meeting. Compared to a monthly or quarterly specification, this has the advantage that it prevents endogeneity issues related to the impact of monetary policy on uncertainty that is evidenced by Mumtaz and Theodoridis (2019): at the meeting frequency there is simply no time for the policy decisions to affect uncertainty. Our baseline sample covers FOMC meetings in the period 1969 – 2008. We also estimate policy reaction functions separately on the periods 1969 – 1979 and 1987 – 2008.

We have three main results. First, U.S. monetary policy is significantly affected by macroeconomic uncertainty. On the full sample, the linear response to a one-standard-deviation increase in macroeconomic uncertainty is a decrease in the intended funds rate of 7 basis points.

Second, we find that instead of a linear response, the role of macroeconomic uncertainty is best captured in terms of low- and high-uncertainty regimes. The Fed sets a funds rate that is 14 basis points lower in a high-uncertainty regime than in a low-uncertainty regime. When calculating the probability of being in a high-uncertainty regime with output or inflation uncertainty, the differences between the two regimes are 17 and 16 basis points, respectively.

Third, financial uncertainty, as proxied by the VXO index, plays a significant role in monetary policy that is separate from the one played by macroeconomic uncertainty. On the full sample, a one-standard-deviation increase in the VXO index is associated with a decrease in the intended funds rate of 4.3 basis points.

We contribute to two strands of literature. The first is on risk management in monetary policy. We discuss the two contributions that are closest to ours. First, Evans et al. (2016) also investigate the role of uncertainty in monetary policy by estimating a battery of monetary policy reaction functions. They first estimate reaction functions at the meeting frequency, using uncertainty indicators that are based on FOMC meeting notes.[4] They find that the funds rate is about 8 basis points higher under uncertainty. This stands in stark contrast with our result of a lower funds rate under uncertainty over a similar sample (their sample is comparable to our later subsample, starting with the onset of Greenspan's tenure as chair). Evans et al. also estimate quarterly reaction functions with various uncertainty proxies.[5] Note that such a specification might suffer from endogeneity issues due to the simultaneous impact of monetary policy on uncertainty (as we discussed earlier). They find mixed results, with some uncertainty measures associated with sizeable decreases and other proxies with significant increases in the funds rate.

We highlight three important differences in the identification procedure that may explain the contrast between our results and those of Evans et al. (2016). First of all, we include a specific measure of macroeconomic uncertainty, while their FOMC-based indicator (as well as some of their uncertainty proxies) potentially mixes financial and macroeconomic uncertainty. Second, we include more explanatory variables in the reaction function, and financial and macroeconomic uncertainty measures at the same time, which allows us to disentangle their effects. Evans et al. on the other hand, enter

[4] Evans et al. (2016) also use forecast revisions as an uncertainty proxy for meeting-by-meeting estimates. They argue that revisions are often caused by unusual events that are difficult to interpret, thereby raising uncertainty. We would argue however, that revisions reflect newly available information, which could either increase or decrease uncertainty. We include revisions in the reaction function together with the uncertainty measures.

[5] These include financial uncertainty proxies, like the VXO index, an uncertainty measure by Jurado et al. (2015) that combines macroeconomic and financial uncertainty, and a number of measures based on the Survey of Professional Forecasters (SPF). The uncertainty proxy used by Evans et al. that comes closest to our measure, is the one introduced by Jurado et al. (2015). Contrary to our measure, it uses revised data, takes a frequentist approach and combines financial and macroeconomic uncertainty.

one uncertainty measure at a time. Third, we use the intended funds rate instead of the realized, effective rate. This accounts for the fact that the Fed does not have full control over the interest rate.

Second, Gnabo and Moccero (2015) estimate non-linear monetary policy reaction functions that allow for different responses in regimes of high and low uncertainty. They measure uncertainty by dispersion in SPF inflation forecasts or by the VXO. Their sample spans the period from the start of Greenspan's tenure to the end of 2005. They find that monetary policy reacts more aggressively to the output gap in high-uncertainty regimes (for both uncertainty measures), but they find no difference for inflation forecasts. We do not identify the effect of uncertainty on the response to specific forecasts, but we complement their study by disentangling the direct response to different types of uncertainty. Together, these studies support the broader notion that uncertainty affects monetary policy.

Methodologically, we also contribute to the literature that studies macroeconomic uncertainty. In this literature, our work comes closest to Orlik and Veldkamp (2014), who also use a Bayesian approach and real-time data to study uncertainty. Their goal is not to introduce the most appropriate measure, but to explain why macroeconomic uncertainty fluctuates. They use non-normal priors for a simple model of GDP growth, and show that changing estimates of disaster risk lead to large and countercyclical uncertainty fluctuations. Our model includes inflation and the interest rate in addition to output growth, and we find substantial countercyclical fluctuations in our macroeconomic uncertainty measure even though we use normal priors.

2. Method

2.1. Data

For the monetary policy reaction function, we use data on changes to the intended federal funds rate around FOMC meetings. Before 1997, this data is provided by Romer and Romer (2004). The period from 1997 onwards is covered by data published by St.

Louis Federal Reserve Bank Economic Data (FRED), which is based on FOMC meeting transcripts and statements. We also collect data on economic projections produced by the staff at the Board of Governors of the Federal Reserve System (Greenbook forecasts). These are the forecasts available to the FOMC meeting members. Specifically, we include forecasts for the quarterly average of the unemployment rate and for annualized quarter-on-quarter real output growth and inflation, as published by the Federal Reserve Bank of Philadelphia.[6]

Our baseline sample covers the FOMC meetings in the period January 1969 – October 2008. The January 1969 meeting is the first meeting for which intended funds rate data is provided by Romer and Romer. The October 2008 meeting is the last meeting before the ZLB was hit. We exclude the ZLB period, because it cannot be modelled by a reaction function intended to describe conventional monetary policy. The period after the funds rate moved away from the zero lower bound is excluded from the analysis, because it is not covered by our Greenbook data.

For the calculation of our macroeconomic uncertainty measure, we construct a real-time dataset. This dataset consists of vintages of the available data at the time of each FOMC meeting. Each vintage can be different because new data is released, or old data is revised. It contains quarterly data for the effective federal funds rate and for quarter-on-quarter annualized real output growth and inflation.

The Philadelphia Fed provides real-time output and price index data. This data consists of monthly vintages that reflect the data available in the middle of the associated month. Vintages for the first month of quarter t have observations for 1947Q1 up to and including quarter $t-2$. Vintages associated with the second and third month of the quarter span the period from 1947Q1 up to and including quarter $t-1$.[7]

Apart from forecasts, the Greenbook data contains historical values for up to four

[6] Wieland and Yang (2020) report some errors in this data as published by the Philadelphia Fed. We adopt their corrections after double checking, and include some of our own corrections based on Greenbook and supplement documents.

[7] Some vintages have a later starting date. Specifically, the December 1991 – December 1992 and November 1999 – March 2000 vintages start in 1959Q1, while the January 1996 – April 1997 vintages start in 1959Q3.

quarters before each Greenbook is released. We carefully match vintages to meetings by comparing these historical values to the corresponding observations in the real-time dataset. However, because most vintage dates do not match exactly with the Greenbook release dates, some differences remain, especially in the most recent observation at the time (the quarter before the Greenbook is released). To ensure that our data accurately reflects the information available to the FOMC meeting participants, we replace observations in the vintage with historical Greenbook values as far as they are available.

More recent information about the state of the economy may be available at the time of each meeting than is captured by its associated vintage. This is due to higher-frequency data like the unemployment rate and industrial production. This additional information may affect the uncertainty felt by the meeting members. To take this into account, while keeping the model simple, we include the information implicitly. We do this by adding to each vintage the Greenbook projections for all quarters up to and including the quarter in which the meeting takes place. As a robustness test, we repeat our analysis without adding the Greenbook projection for the current quarter.

Funds rate data is provided by FRED. Funds rate projections are not included in the Greenbook dataset, but the Philadelphia Fed does publish a separate dataset with the funds rate assumptions underlying the Greenbook forecasts. This data is available for meetings in the period 1981Q1 – 2008Q3. For the remainder of the sample, we estimate the current funds rate by using the available monthly funds rate data from before the meeting, and assume that it stays at the target rate level immediately before the meeting for the remainder of the quarter.[8]

The inflation and federal funds rate series are differenced to make them approximately stationary. All data is standardized using the mean and standard deviation computed over the vintage after the historical values have been replaced. Their calculation excludes the two most recent observations however, so they do not use projections for the current and previous quarters. Funds rate data is available only from 1954Q3 onwards, which

[8]For the period where the Greenbook assumptions are available, our estimate for the current quarter funds rate is very similar, with a correlation coefficient between the two of 0.9994.

means that after differencing and including Greenbook projections, each vintage covers data from 1954Q4 up to and including the quarter the meeting takes place. Henceforth, when we refer to the vintage associated with a meeting, we refer to these adjusted vintages, and not to the original vintages provided by the Philadelphia Fed.

We proxy financial uncertainty with the VXO index on the Greenbook release day. VXO data is only available from 1986 onwards. Following standard practice (e.g., Bloom, 2009), we approximate it by the 30-day standard deviation of S&P500 daily returns before 1986. The realized volatility series is standardized to have the same mean and variance as the VXO index over the period where they overlap.

2.2. Construction of macroeconomic uncertainty measure

For each FOMC meeting, we estimate a simple monetary VAR with time-varying parameters (TVP-VAR) on the associated real-time data vintage. Using a Bayesian approach, we derive the posterior density of one-quarter-ahead forecasts. We compute uncertainty as the differential entropy of this density. The priors for the VAR coefficients and the degree of their time-variability are determined by three hyperparameters. We find reasonable values for these hyperparameters by fitting the TVP-VAR forecasts for output growth and inflation at every FOMC meeting to the corresponding Greenbook forecasts.

2.2.1. Bayesian time-varying parameter VAR

Consider one of the real-time data vintages (corresponding to one of the FOMC meetings), with T quarterly observations indexed by $t = 1, 2, \ldots, T$. The TVP-VAR consists of annualized quarter-on-quarter real output growth (y_t), the first difference of annualized quarter-on-quarter inflation ($\Delta\pi_t$), and the first-differenced effective federal funds rate (Δi_t). As is standard in quarterly VARs, we include four lags.[9]

[9] An alternative to using a fixed number of lags would be to use an information criterion like BIC to select a lag length. However, Stock and Watson (2002) show that a similar VAR performs better with a fixed lag length of four, than with a BIC-selected lag length.

We define $x_t = (y_t, \Delta\pi_t, \Delta i_t)'$ and write the TVP-VAR as

$$x_t = Z_t\beta_t + \epsilon_t, \tag{1a}$$

$$\beta_t = \beta_{t-1} + q_t, \tag{1b}$$

with $\epsilon_t \sim \mathcal{N}(0, \Sigma_t)$, $q_t \sim \mathcal{N}(0, Q_t)$, β_t the time-varying coefficient vector, and

$$Z_t = I_3 \otimes X_{t-1}, \quad X_{t-1} = (1, x'_{t-1}, \ldots, x'_{t-4}).$$

We adopt the Bayesian estimation approach of Koop and Korobilis (2013). It uses the Kalman filter, which is a recursive estimator. Consider $\tau \in \{1, \ldots, T\}$. Given a normal prior for the coefficient vector β_0, and Σ_t and Q_t for $t = 1, \ldots, \tau$, the Kalman filter gives expressions for the posterior mean $\beta_{\tau|\tau}$ and covariance matrix $V_{\tau|\tau}$ of the coefficient vector, conditional on the observations through time τ:[10]

$$\beta_\tau | x_1, x_2, \ldots, x_\tau \sim \mathcal{N}\left(\beta_{\tau|\tau}, V_{\tau|\tau}\right). \tag{2}$$

For $\tau = T$, this corresponds to the posterior conditional on all observations in the vintage. This is the posterior we use in the uncertainty calculation later on.

We denote the prior mean and covariance matrix by $\beta_{0|0}$ and $V_{0|0}$, respectively:

$$\beta_0 \sim \mathcal{N}\left(\beta_{0|0}, V_{0|0}\right).$$

We use the same prior as Koop and Korobilis, which is a variant of the classical Minnesota prior (Doan et al., 1984; Litterman, 1986). Because we transform the variables in our VAR to approximate stationarity in our data setup, we set $\beta_{0|0} = 0$. We define $V_{0|0}$ to

[10] We use the standard Kalman filtering formulae (see, e.g., Durbin and Koopman, 2012).

be diagonal, with diagonal elements $V_{0|0}^{ii}$:

$$V_{0|0}^{ii} = \begin{cases} \dfrac{\gamma}{l^2} & \text{for coefficients on lag } l = 1, \dots, 4; \\ 100 & \text{for the intercepts.} \end{cases} \tag{3}$$

The overall tightness of the prior is determined by the parameter γ. The prior on coefficients of older lags is tighter than that for more recent lag coefficients: The assumption is that older lags have a smaller impact on the current value, compared to more recent ones.

We follow Koop and Korobilis in replacing Σ_t and Q_t by estimates, denoted by $\widehat{\Sigma}_t$ and $\widehat{Q}_t$. This has the advantage that no priors have to be defined for these covariance matrices, and that no computationally expensive MCMC methods are required. We denote the resulting estimates for the posterior mean and covariance matrix by $\widehat{\beta}_{t|t}$ and $\widehat{V}_{t|t}$.

First, we estimate Σ_t with an exponentially weighted moving average with decay factor $0 \leq \kappa \leq 1$:

$$\widehat{\Sigma}_t = \kappa \, \widehat{\Sigma}_{t-1} + (1 - \kappa) \, \widehat{\epsilon}_t \widehat{\epsilon}_t'. \tag{4}$$

Here, the Kalman filter gives the estimated residual $\widehat{\epsilon}_t = x_t - Z_t \beta_{t|t}$. The decay factor determines the degree of time-variability of Σ_t: The larger κ, the slower the dynamics. In the extreme case where $\kappa = 1$, the covariance matrix is constant. Following Koop and Korobilis, we use the sample covariance matrix of the whole vintage as the initial value $\widehat{\Sigma}_0$.

Second, we posit that $\widehat{Q}_t = \left(\lambda^{-1} - 1\right) \widehat{V}_{t-1|t-1}$, where $0 < \lambda \leq 1$ is called the forgetting factor. The forgetting factor determines the amount of weight put on older observations compared to the current one. A larger λ implies that the coefficient vector β_t changes slower.

2.2.2. *Calculating uncertainty*

The Kalman filter provides us with estimates for the posterior mean $\widehat{\beta}_{T|T}$ and covariance matrix $\widehat{V}_{T|T}$ conditional on all the data contained in the vintage. The estimated density for the coefficient vector in the next quarter (β_{T+1}) is given by

$$\widehat{\beta}_{T+1}|x_1, \ldots, x_T \sim \mathcal{N}\left(\widehat{\beta}_{T+1|T}, \widehat{V}_{T+1|T}\right),$$

with mean and covariance matrix given by (1b):

$$\widehat{\beta}_{T+1|T} = \widehat{\beta}_{T|T}, \quad \widehat{V}_{T+1|T} = \widehat{V}_{T|T} + \widehat{Q}_{T+1} = \lambda^{-1}\widehat{V}_{T|T}.$$

Since Z_{T+1} is known, it follows that the posterior forecast for the state of the economy one quarter ahead (x_{T+1}) is normal, with mean x^F_{T+1} and covariance matrix $\widehat{R}_{T+1}$ given by

$$x^F_{T+1} = Z_{T+1}\,\widehat{\beta}_{T+1|T}, \quad \widehat{R}_{T+1} = Z_{T+1}\,\widehat{V}_{T+1|T}\,Z'_{T+1}.$$

Recall however, that the inflation and interest rate series are differenced, and that all variables in the VAR are standardized. We transform back to non-standardized forecasts of the series that are included in the Greenbook, because these are the forecasts the policymakers are concerned with. We denote the non-standardized, non-differenced version of x_t by $\widetilde{x}_t$. We define $\widehat{\mu}_x$ to be the mean used to standardize x, and $\widehat{\Sigma}_x$ to be the matrix with the standard deviations used to standardize x on its diagonal. Furthermore defining $\chi_t = (0, \pi_t, i_t)'$, it follows that the estimated posterior density of forecasts for $\widetilde{x}_{T+1}$ is normal, with mean $\widetilde{x}^F_{T+1}$ and covariance matrix $\widetilde{R}_{T+1}$ given by

$$\widetilde{x}^F_{T+1} = \chi_T + \widehat{\Sigma}_x\,x^F_{T+1} + \widehat{\mu}_x, \quad \widetilde{R}_{T+1} = \widehat{\Sigma}_x\widehat{R}_{T+1}\widehat{\Sigma}'_x.$$

We now denote the length of the vintage corresponding to FOMC meeting m by T_m, and its associated posterior mean and covariance matrix by $\widetilde{x}^F_{m,T_m+1}$ and $\widetilde{R}_{m,T_m+1}$. We define the macroeconomic uncertainty measure, denoted by U_{Mm}, as the differential entropy[11] of the posterior density of one-quarter-ahead forecasts:

$$U_{Mm} = \frac{3}{2} + \frac{3}{2}\log 2\pi + \frac{1}{2}\log\det \widetilde{R}_{m,T_m+1}. \tag{5}$$

This entropy takes into account the covariance between the forecasts of different variables. The last term in equation (5) can be rewritten as

$$\frac{1}{2}\log\det \widetilde{R}_{m,T_m+1} = \sum_{i=1}^{3} \log\left(\sqrt{eig_{im}}\right), \tag{6}$$

where eig_{im} are the eigenvalues of the covariance matrix $\widetilde{R}_{m,T_m+1}$. The square roots of these eigenvalues give the standard deviations along the orthogonal components of maximum variation (the principal components, given by the corresponding eigenvectors). Larger covariances lead to a smaller differential entropy.[12]

In addition to this aggregate measure of macroeconomic uncertainty, we assess the policy reaction to the uncertainty surrounding the forecasts for individual series. In particular, we consider the posterior standard deviation of the one-quarter-ahead forecasts of output growth (U_{ym}) and inflation ($U_{\pi m}$). These are computed as the square root of the corresponding diagonal element in the covariance matrix of the posterior density of forecasts ($\widetilde{R}_{m,T_m+1}$).

2.2.3. Choosing hyperparameters

Before we move to the monetary policy reaction function, let us note that the TVP-VAR contains three hyperparameters: the forgetting factor λ, the decay factor κ, and the tightness parameter γ. We fit these hyperparameters to the Greenbook data by

[11] Differential entropy, a concept from information theory, is defined as

$$-\int f(x)\log f(x)\,dx,$$

where $f(x)$ is the probability density function. An expression in the case of a multivariate normal distribution is given by Ahmed and Gokhale (1989).

[12] This entropy measure is similar to a measure of forecasting performance that is sometimes used, namely, the log determinant of the covariance matrix of forecast errors (e.g., Smets and Wouters, 2007).

constrained maximum likelihood estimation of the following model:

$$\begin{pmatrix} y^{GB}_{m,T_m+1} \\ \pi^{GB}_{m,T_m+1} \end{pmatrix} = \begin{pmatrix} \widetilde{y}^{F}_{m,T_m+1}(\lambda,\kappa,\gamma) \\ \widetilde{\pi}^{F}_{m,T_m+1}(\lambda,\kappa,\gamma) \end{pmatrix} + e_m, \tag{7a}$$

$$e_m = \overline{e} + P\, e_{m-1} + \eta_m, \tag{7b}$$

where $\eta_m \sim \mathcal{N}(0, S)$. Here, we emphasize the dependence of the TVP-VAR forecasts on the hyperparameters, and indicate the one-quarter-ahead forecasts for output and inflation included in the Greenbook for meeting m by y^{GB}_{m,T_m+1} and π^{GB}_{m,T_m+1}, respectively. This model assumes that differences between the Greenbook and TVP-VAR forecasts follow a VAR(1) process. This means that it can take into account any first-order serial and cross-correlations in these differences. This approach is similar to how Milani (2011) fits a comparable learning model to forecasts from the SPF.

We let $0.94 \leq \kappa \leq 0.98$, following Koop and Korobilis (2013), while λ and γ are constrained to the unit interval. We only include meetings from the period January 1969 – October 2008 in the estimation (the same period we use for estimation of the monetary policy reaction function). The meetings before the starting date are excluded because we do not have intended funds rate data for them, and hence have less reliable estimates for the current federal funds rate. We also exclude the meetings after October 2008 for which the ZLB is binding.

As a robustness exercise, we repeat our analysis for reasonable deviations from the maximum likelihood hyperparameters.

2.3. Monetary policy reaction function

To identify the impact of macroeconomic uncertainty on monetary policy, we estimate the monetary policy reaction function used by Romer and Romer (2004), augmented with uncertainty measures:

$$\begin{aligned}\Delta ff_m = \gamma_0 + \gamma_b ffb_m + \sum_{i=-1}^{2} \gamma_{yi}\, y_{mi}^{GB} + \sum_{i=-1}^{2} \gamma_{\pi i}\, \pi_{mi}^{GB} + \gamma_{u0}\, u_{m0}^{GB} \\ + \sum_{i=-1}^{2} \delta_{yi}\, \Delta y_{mi}^{GB} + \sum_{i=-1}^{2} \delta_{\pi i}\, \Delta \pi_{mi}^{GB} + \phi_{VXO}\, VXO_m + \phi_U\, U_m + v_m.\end{aligned} \tag{8}$$

Here, Δff_m indicates the change in the intended federal funds rate around FOMC meeting m, and ffb_m refers to the intended funds rate before any changes related to that meeting. This lagged interest rate can capture any mean-reverting behaviour of the intended funds rate.

We indicate Greenbook forecasts for meeting m by y_{mi}^{GB} (output growth), π_{mi}^{GB} (inflation) and u_{mi}^{GB} (unemployment), where i indicates the horizon relative to meeting m: $i = -1$ corresponds to the previous quarter, $i = 0$ to the current quarter, and $i = 1$ and $i = 2$ to the the one-quarter- and two-quarters-ahead forecasts, respectively.[13] Projections for the previous quarter account for lagged economic conditions, while unemployment forecasts are included because maximum sustainable employment is one of the explicit goals of the Fed.

The reaction function also includes forecast revisions $\Delta y_{mi}^{GB} = y_{mi}^{GB} - y_{m-1,i}^{GB}$, with a similar definition for $\Delta \pi_{mi}^{GB}$. Here, the forecasts refer to the same quarter: For example, if meeting m takes place in quarter t, while meeting $m-1$ took place in the quarter before $(t-1)$, the forecast revision Δy_{m0}^{GB} is calculated using the meeting m forecast for the current quarter and the one-quarter-ahead forecast from meeting $m-1$. Both are forecasts for quarter t. These forecast revisions are likely to impact the intended interest rate. Suppose that the rate setting decision at the previous meeting was based on forecasts that now have been extensively revised. This might lead to a change in the interest rate that is larger than just explained by the level of the new forecasts and the interest rate lag.

[13] In many cases, a first release for previous quarter data is already available, and hence is not a forecast.

Most importantly for our analysis, we include financial and macroeconomic uncertainty in the monetary policy reaction function. Including both allows us to disentangle the response to financial uncertainty, which has already been established in the literature, from that to macroeconomic uncertainty. The VXO at the time of meeting m is denoted by VXO_m. We consider several variants of the reaction function that differ in terms of the macroeconomic uncertainty measure (U_m) that is included. Our main specification uses the entropy measure of aggregate uncertainty ($U_m = U_{Mm}$), but we also estimate the reaction to uncertainty related to output growth ($U_m = U_{ym}$) and inflation ($U_m = U_{\pi m}$). We do not consider interest rate uncertainty, because funds rate forecasts are not as relevant for monetary policymakers (since they are the ones who determine the future rate).

In addition to estimating a linear relationship between the uncertainty measures and the interest rate, we consider a non-linear transformation that aims to measure the probability of being in a high-uncertainty regime. We adopt the logistic function used by Falck et al. (2019) in the context of regimes of disagreement among forecasters. It gives the probability of being in a high-uncertainty regime as a function of the uncertainty measure U_m:

$$F(U_m) = \frac{\exp\left(\theta \frac{U_m - c}{\sigma_U}\right)}{1 + \exp\left(\theta \frac{U_m - c}{\sigma_U}\right)}, \tag{9}$$

where c is the median and σ_U the standard deviation of U. The parameter θ controls how strongly the probability responds to changes in uncertainty. Such a specification is also considered by Gnabo and Moccero (2015) to identify uncertainty regimes. However, instead of estimating the parameters, we follow Falck et al. (2019) in choosing $\theta = 5$ and assessing our results' robustness to changing its value.[14] The function values lie between zero and one, and the corresponding coefficient in the reaction function gives the effect of being in a high-uncertainty regime.

Lastly, v_m is an error term.

[14]We also consider the special case where $F(U_m)$ is a dummy variable that equals one when the uncertainty measure is above its median and zero otherwise.

We estimate the reaction function (8) by least squares on the full sample, as well as on two subsamples. The first subsample is characterized by the tenure of Martins, Burns, and Miller as chairmen of the Fed, and covers meetings in the period 14 January 1969 – 11 July 1979. The second subsample covers Greenspan's tenure, as well as part of Bernanke's. It spans meetings between 18 August 1987 and 29 October 2008.[15] For these subsamples, we separately re-standardize the uncertainty measures and re-calculate the probabilities of being in a high-uncertainty regime.

These two subsamples exclude the period October 1979 – October 1982 in which the Fed stopped targeting the funds rate, and targeted non-borrowed reserves instead. While Romer and Romer (2004) include this period in their estimation, others have argued that it can lead to biased results (Coibion and Gorodnichenko, 2011; Coibion, 2012).[16] By both including and excluding this period, we can investigate to what extent the results are driven by this period.

3. Results

3.1. Real-time macroeconomic uncertainty

We find the following maximum likelihood hyperparameters:

$$\lambda^* = 1, \quad \kappa^* = 0.98, \quad \gamma^* = 0.0307.$$

This value for λ corresponds to the constant coefficient case: Older observations receive the same weight as current observations. The value for κ means that the covariance matrix of the VAR error term changes relatively slowly. These hyperparameters are in

[15]These two samples are also used by Caggiano et al. (2018), and like our second subsample, the sample of Evans et al. (2016) starts with the beginning of Greenspan's tenure as chairman.

[16]Romer and Romer (2004) note that even in this period, the Fed was concerned about the federal funds rate, and discussed its behaviour. They argue that the change in the intended funds rate therefore is the easiest indicator of monetary policy over a long timespan where monetary policy has changed. However, Coibion (2012) suggests that this is the period where the identification is most likely to be misspecified. He shows that the results of Romer and Romer (2004) are highly sensitive to excluding the period of non-borrowed reserves targeting. This is partly due to the fact that this period contains the largest funds rate changes in the sample.

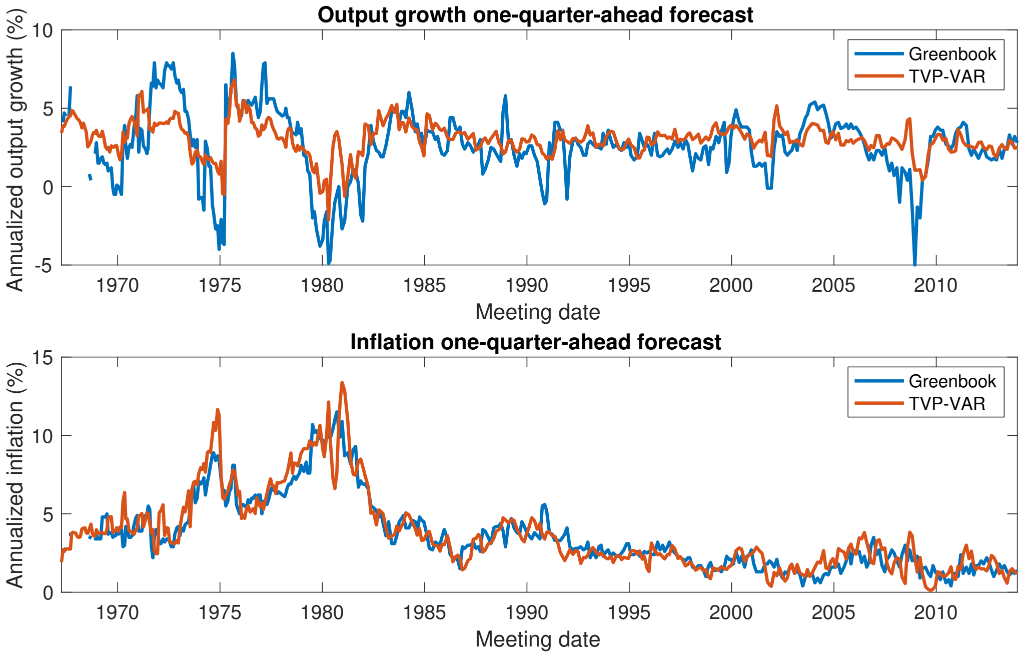

Figure 1: Comparison between one-quarter-ahead forecasts provided by the TVP-VAR and by the Greenbook for output growth (*Top*) and inflation (*Bottom*).

line with what Koop and Korobilis (2013) find to be the optimal parameters for a small monetary TVP-VAR.[17]

We provide a comparison of the TVP-VAR forecasts conditional on these parameters with those provided by the Greenbook in Figure 1. The model forecasts seem to be a decent approximation of the Greenbook forecasts. The correlation between the two forecast series is 0.72 ($p = 0$) for output growth and 0.92 ($p = 0$) for inflation. The largest deviations between the model and Greenbook forecasts occur in periods of rapid, large change in the economic outlook, especially for the output growth forecasts. This is understandable given the fact that the VAR models the economy as a mean-reverting

[17] Koop and Korobilis (2013) estimate (among other models) a similar small TVP-VAR, but with inflation measured by the consumer price index, and allowing the hyperparameters to change over time. They find that $\lambda = 1$ is optimal most of the time, with some periods of $\lambda = 0.99$ before 1985, and a brief period of $\lambda = 0.98$ in the early 1980s. They find an optimal $\gamma = 0.05$, apart from two periods in the mid-1980s, where $\gamma = 0.1$ is optimal. We explore the robustness of our results to changing the hyperparameters within these bounds. Koop and Korobilis do not report how the optimal decay factor evolves over time, but they allow for $\kappa \in \{0.94, 0.96, 0.98\}$.

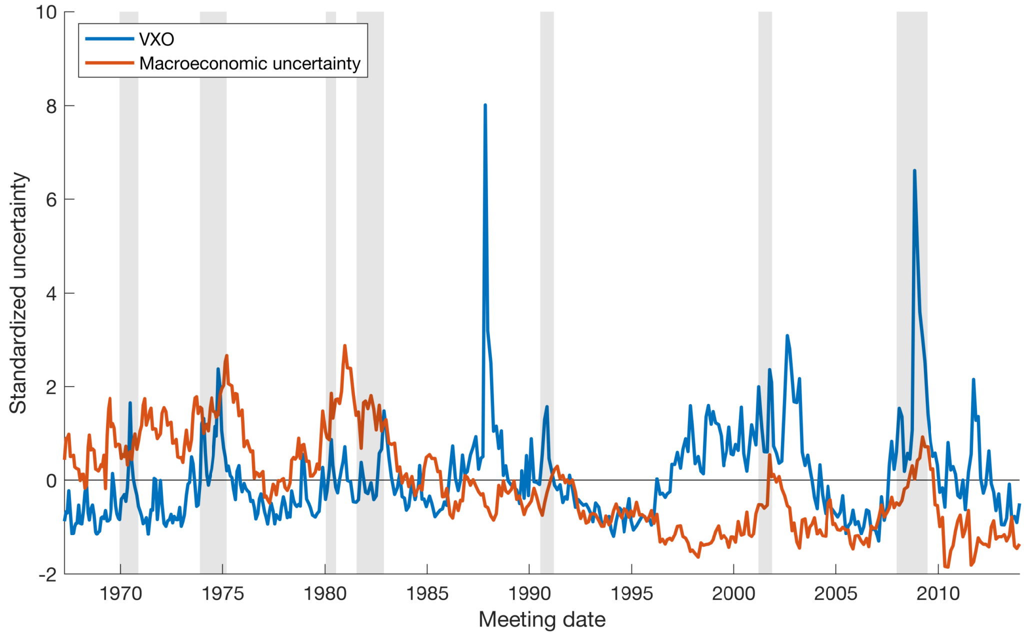

Figure 2: Financial uncertainty proxy (VXO index) and entropy measure of macroeconomic uncertainty. Both series are standardized to have zero mean and unit standard deviation. The grey bars indicate NBER recessions.

process, which is not a good model for those periods.

In Figure 2, we plot the resulting entropy-based macroeconomic uncertainty measure, together with the VXO index, which we use as financial uncertainty proxy. Figure A.4 in the appendix plots the uncertainties for the individual series included in the TVP-VAR. Note that although our baseline sample for the policy reaction estimation runs from January 1969 to October 2008, we calculate macroeconomic uncertainty on the whole Greenbook sample, spanning the period March 1967 – December 2013. Several characteristics stand out.

First, and most importantly for our analysis, there seems to be no clear relationship between the two types of uncertainty. The correlation coefficient between financial and macroeconomic uncertainty is small (-0.06) and insignificant ($p = 0.18$).[18] This helps us disentangle the role that both types of uncertainty play in monetary policy.

[18]The correlation of the VXO with output growth uncertainty is -0.07 ($p = 0.15$), and with inflation uncertainty -0.12 ($p = 0.01$).

Second, macro-uncertainty is persistent: A first-order autoregression yields an AR(1) coefficient of 0.96 ($p = 0$). The AR(1) coefficient for financial uncertainty is 0.66 ($p = 0$). Third, there are few times where macro-uncertainty peaks. Most prominent are the recession of 1974–75, the early 1980s recession, the 2001 recession, and the Great Recession of 2008–09. This leads to a fourth observation: Uncertainty tends to rise before recessions, and peak during or shortly after them.

Lastly, the figure shows a downward trend in macroeconomic uncertainty, with most observations above the mean in the first half of the sample. This is partly explained by the decreasing volatility of the economic time series, and partly by the constant-coefficient nature of the underlying model ($\lambda = 1$): Every additional observation gives new information about the fixed coefficients, thereby lowering the uncertainty surrounding the coefficient estimates. As the real-time sample grows over time, uncertainty decreases.

3.2. Monetary policy response to uncertainty

In Table 1, we present our full sample estimates for the monetary policy reaction function with the entropy measure of macroeconomic uncertainty (U_{Mm}). Both the VXO index and the macro-uncertainty measure are standardized to have zero mean and unit standard deviation.[19] This means that their respective coefficients measure the policy response in terms of standard deviations.

For clarity, we only report the net total effect for some groups of variables.[20] For example, we report for the level of the output growth forecasts that the sum of their coefficients (γ_{yi}) over the different horizons (previous quarter, current quarter, one-quarter-ahead, two-quarters-ahead) is 0.053. The sum of the coefficients for revisions to the output growth forecasts is 0.173. This means that the net effect of a one percentage point increase compared to the previous meeting in the output growth forecast for each horizon, is an increase in the intended funds rate of about 23 basis points.

[19]We standardize over the whole Greenbook sample, so that the series used in the estimation are the same as those plotted in Figure 2.

[20]Full results are available upon request.

Table 1: Reaction function estimates on full sample using entropy uncertainty

	Linear			Regime		
	Coeff	SE	p	Coeff	SE	p
Intercept	−0.063	0.103	0.543	0.037	0.093	0.691
γ_b	−0.012	0.010	0.216	−0.013	0.010	0.218
$\sum_{i=-1}^{2} \gamma_{yi}$	0.053	0.020	0.007	0.055	0.020	0.006
$\sum_{i=-1}^{2} \gamma_{\pi i}$	0.055	0.016	0.001	0.051	0.017	0.003
γ_{u0}	−0.038	0.014	0.007	−0.042	0.015	0.005
$\sum_{i=-1}^{2} \delta_{yi}$	0.173	0.047	0.000	0.173	0.048	0.000
$\sum_{i=-1}^{2} \delta_{\pi i}$	0.018	0.076	0.808	0.024	0.075	0.751
ϕ_{VXO}	−0.043	0.015	0.005	−0.044	0.015	0.004
ϕ_U	−0.074	0.034	0.032	−0.137	0.059	0.021
N		360			360	
RMSE		0.344			0.345	
$\overline{R}^2$		0.261			0.258	

Note. The full sample spans FOMC meetings in the period 14 January 1969 – 29 October 2008. The left panel presents estimates for our reaction function (8) with the entropy uncertainty measure: $U_m = U_{Mm}$. The right panel presents estimates with the probability of being in a high-uncertainty regime given by (9): $U_m = F(U_{Mm})$. The VXO and entropy uncertainty series are standardized prior to estimation. Reported standard errors and p-values are robust to heteroscedasticity and autocorrelation, estimated with Bartlett kernel and data-driven bandwidth estimated with AR(1) model by maximum likelihood (Andrews, 1991).

Starting with the left panel of Table 1, we see that the policy reaction to financial uncertainty, as measured by the VXO index, is negative and significant at the 1% level. The effect size is about 4 basis points per standard deviation. The reaction to macroeconomic uncertainty is also significantly negative (at the 5% level), with a one-standard-deviation increase leading to an intended fall in the funds rate of 7.4 basis points. This is comparable to the response to an increase in the unemployment rate of two percentage points.

The right panel of Table 1 shows our estimates when we replace the macro-uncertainty measure in the reaction function by the probability of being in a high-uncertainty regime ($U_m = F(U_{Mm})$). In Figure 3, we plot the evolution of that probability over the sample. Most high-uncertainty episodes lie in the first half of the sample. The reaction to the VXO index is virtually the same in the specification with regime probabilities. Furthermore, the estimates indicate that the intended interest rate lies almost 14 basis points lower in the high-uncertainty regime compared to the low-uncertainty regime. This is relatively

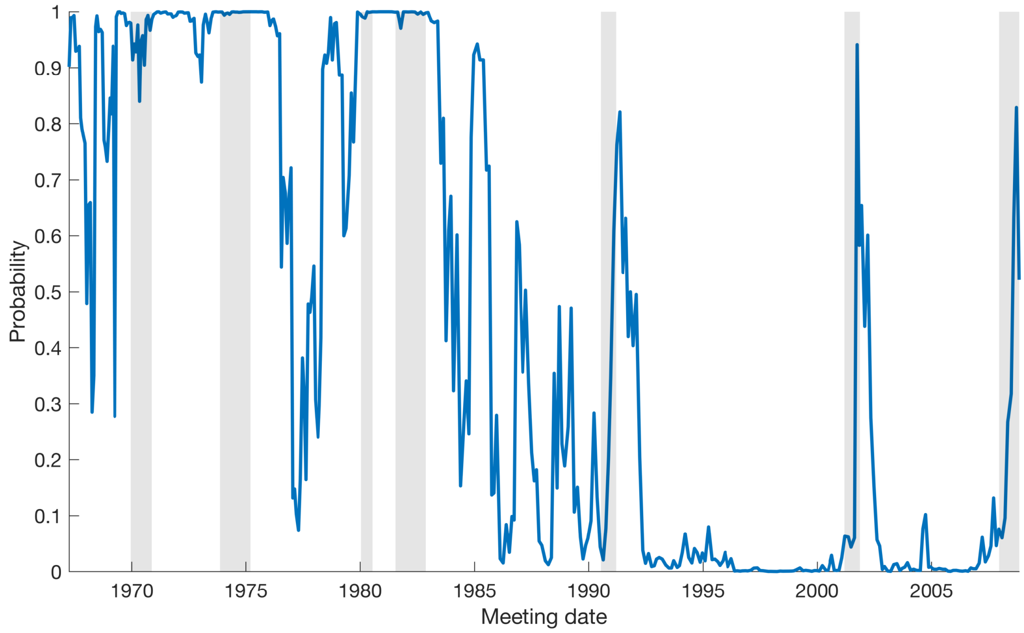

Figure 3: Probability of being in a high-uncertainty regime, as defined in terms of entropy uncertainty. The grey bars indicate NBER recessions.

large compared to the most common policy move of 25 basis points.

Because our entropy measure captures multiple components of macroeconomic uncertainty, we study whether the Fed reacts differently to each of those components. To investigate this possibility, we look at the response to output growth and inflation uncertainty separately.

We start with the reaction function that includes the output growth uncertainty measure (U_{ym}). The full sample estimates (Table 2) show that the linear relationship between macro-uncertainty and the intended funds rate is significant at the 10% level. This may partly be explained by the logarithmic transformation in the calculation of the entropy uncertainty measure. This transformation dampens the high uncertainty peaks in the 1970s and 1980s compared to those later in the sample. Something similar happens with the calculation of the regime probabilities, which might explain why the regime specification still leads to a significant response. In fact, the effect is even larger than for the entropy-based probabilities: being in a high-uncertainty regime is associated

Table 2: Reaction function estimates on full sample using output growth uncertainty

	Linear			Regime		
	Coeff	SE	p	Coeff	SE	p
Intercept	−0.001	0.089	0.991	0.060	0.090	0.505
γ_b	−0.014	0.010	0.153	−0.013	0.010	0.191
$\sum_{i=-1}^{2} \gamma_{yi}$	0.053	0.020	0.009	0.056	0.020	0.005
$\sum_{i=-1}^{2} \gamma_{\pi i}$	0.053	0.016	0.001	0.055	0.017	0.002
γ_{u0}	−0.046	0.015	0.002	−0.045	0.015	0.003
$\sum_{i=-1}^{2} \delta_{yi}$	0.176	0.047	0.000	0.173	0.048	0.000
$\sum_{i=-1}^{2} \delta_{\pi i}$	0.018	0.075	0.814	0.021	0.075	0.777
ϕ_{VXO}	−0.044	0.015	0.004	−0.043	0.015	0.005
ϕ_U	−0.067	0.038	0.080	−0.169	0.066	0.011
N		360			360	
RMSE		0.344			0.344	
$\overline{R}^2$		0.261			0.261	

Note. The full sample spans FOMC meetings in the period 14 January 1969 – 29 October 2008. The left panel presents estimates for our reaction function (8) with the output growth uncertainty measure: $U_m = U_{ym}$. The right panel presents estimates with the probability of being in a high-uncertainty regime given by equation (9): $U_m = F(U_{ym})$. The VXO and output growth uncertainty series are standardized prior to estimation. Reported standard errors and p-values are robust to heteroscedasticity and autocorrelation, estimated with Bartlett kernel and data-driven bandwidth estimated with AR(1) model by maximum likelihood (Andrews, 1991).

with a decrease in the intended funds rate of almost 17 basis points.

We present the subsample estimates in Table 3. In the Greenspan-Bernanke sample, a high-uncertainty regime is associated with a highly significant decrease in the intended funds rate of 9 basis points. The response is the same as that to a one-percentage-point increase in the unemployment rate forecast for the current quarter. The response to uncertainty is insignificant on the earlier (Martins-Burns-Miller) sample.

Lastly, we discuss the estimates that use the inflation uncertainty measure ($U_{\pi m}$) in the reaction function. On the full and Martins-Burns-Miller sample, the responses are qualitatively similar as those using output growth uncertainty (see Table 4 and Table 5). On the Greenspan-Bernanke sample however, the effect of being in a high-uncertainty regime, as measured by inflation uncertainty, is statistically indistinguishable from zero (see Table 5).[21] The significant response to output growth uncertainty may be muted by

[21]We compare the high-uncertainty probabilities based on output growth uncertainty with those based

Table 3: Reaction function estimates on subsamples using output growth uncertainty

	Linear			Regime		
	Coeff	SE	p	Coeff	SE	p
Martins-Burns-Miller sample: 14 January 1969 – 11 July 1979						
Intercept	−0.158	0.366	0.668	−0.136	0.367	0.712
γ_b	0.002	0.033	0.960	0.003	0.033	0.936
$\sum_{i=-1}^{2} \gamma_{yi}$	0.068	0.024	0.005	0.067	0.023	0.004
$\sum_{i=-1}^{2} \gamma_{\pi i}$	0.048	0.031	0.125	0.043	0.033	0.198
γ_{u0}	−0.060	0.047	0.206	−0.058	0.047	0.225
$\sum_{i=-1}^{2} \delta_{yi}$	0.089	0.067	0.187	0.090	0.065	0.167
$\sum_{i=-1}^{2} \delta_{\pi i}$	0.218	0.095	0.024	0.227	0.094	0.017
ϕ_{VXO}	−0.070	0.040	0.081	−0.068	0.041	0.098
ϕ_U	−0.000	0.025	0.999	−0.032	0.065	0.621
N		123			123	
RMSE		0.241			0.240	
$\overline{R}^2$		0.321			0.323	
Greenspan-Bernanke sample: 18 August 1987 – 29 October 2008						
Intercept	0.084	0.174	0.630	0.106	0.160	0.508
γ_b	−0.070	0.020	0.001	−0.071	0.018	0.000
$\sum_{i=-1}^{2} \gamma_{yi}$	0.106	0.019	0.000	0.107	0.018	0.000
$\sum_{i=-1}^{2} \gamma_{\pi i}$	0.200	0.044	0.000	0.213	0.041	0.000
γ_{u0}	−0.090	0.027	0.001	−0.091	0.026	0.001
$\sum_{i=-1}^{2} \delta_{yi}$	0.030	0.030	0.313	0.029	0.028	0.293
$\sum_{i=-1}^{2} \delta_{\pi i}$	−0.050	0.066	0.445	−0.058	0.065	0.373
ϕ_{VXO}	−0.028	0.013	0.029	−0.026	0.012	0.038
ϕ_U	−0.019	0.014	0.187	−0.091	0.033	0.006
N		171			171	
RMSE		0.153			0.151	
$\overline{R}^2$		0.526			0.541	

Note. The left panel presents estimates for our reaction function (8) with the output growth uncertainty measure: $U_m = U_{ym}$. The right panel presents estimates with the probability of being in a high-uncertainty regime given by equation (9): $U_m = F(U_{ym})$. The VXO and output growth uncertainty series are standardized on each subsample prior to estimation. Reported standard errors and p-values are robust to heteroscedasticity and autocorrelation, estimated with Bartlett kernel and data-driven bandwidth estimated with AR(1) model by maximum likelihood (Andrews, 1991). The sample dates indicate the first and last FOMC meeting in the sample.

Table 4: Reaction function estimates on full sample using inflation uncertainty

	Linear			Regime		
	Coeff	SE	p	Coeff	SE	p
Intercept	-0.020	0.096	0.837	0.035	0.094	0.711
γ_b	-0.013	0.010	0.182	-0.012	0.010	0.240
$\sum_{i=-1}^{2} \gamma_{yi}$	0.052	0.020	0.010	0.057	0.020	0.005
$\sum_{i=-1}^{2} \gamma_{\pi i}$	0.053	0.016	0.001	0.055	0.018	0.003
γ_{u0}	-0.043	0.014	0.003	-0.044	0.015	0.004
$\sum_{i=-1}^{2} \delta_{yi}$	0.175	0.047	0.000	0.172	0.048	0.000
$\sum_{i=-1}^{2} \delta_{\pi i}$	0.014	0.076	0.857	0.019	0.075	0.797
ϕ_{VXO}	-0.046	0.016	0.004	-0.046	0.016	0.004
ϕ_U	-0.062	0.043	0.143	-0.159	0.072	0.028
N		360			360	
RMSE		0.345			0.345	
$\overline{R}^2$		0.258			0.258	

Note. The full sample spans FOMC meetings in the period 14 January 1969 – 29 October 2008. The left panel presents estimates for our reaction function (8) with the inflation uncertainty measure: $U_m = U_{\pi m}$. The right panel presents estimates with the probability of being in a high-uncertainty regime given by equation (9): $U_m = F(U_{\pi m})$. The VXO and inflation uncertainty series are standardized prior to estimation. Reported standard errors and p-values are robust to heteroscedasticity and autocorrelation, estimated with Bartlett kernel and data-driven bandwidth estimated with AR(1) model by maximum likelihood (Andrews, 1991).

the inflation component of the entropy measure.[22]

3.3. Robustness

Most of our results are robust to deviations from our benchmark specification along various dimensions. The most sensitive result is the linear response to entropy uncertainty on the full sample.

First, we investigate the effect of changing the TVP-VAR hyperparameters within reasonable bounds. Specifically, we recalculate macroeconomic uncertainty for values of the hyperparameters that lie on a $3\times3\times3$-grid:

$$\lambda \in \{0.98, 0.99, 1\}, \quad \kappa \in \{0.94, 0.96, 0.98\}, \quad \gamma \in \{0.01, 0.05, 0.1\}.$$

on inflation uncertainty for the subsamples in Figure A.6 in the appendix.

[22] Using interest rate uncertainty (the third component of the entropy measure) to calculate the probability of being in a high-uncertainty regime, estimates indicate that being in that regime leads to an intended decrease in the interest rate of almost 10 basis points ($p = 0.005$).

Table 5: Reaction function estimates on subsamples using inflation uncertainty

	Linear			Regime		
	Coeff	SE	p	Coeff	SE	p
Martins-Burns-Miller sample: 14 January 1969 – 11 July 1979						
Intercept	−0.158	0.366	0.667	−0.139	0.366	0.704
γ_b	0.002	0.033	0.964	0.002	0.033	0.943
$\sum_{i=-1}^{2} \gamma_{yi}$	0.068	0.024	0.005	0.067	0.023	0.004
$\sum_{i=-1}^{2} \gamma_{\pi i}$	0.048	0.031	0.121	0.044	0.033	0.186
γ_{u0}	−0.060	0.047	0.204	−0.058	0.048	0.226
$\sum_{i=-1}^{2} \delta_{yi}$	0.088	0.067	0.191	0.090	0.065	0.167
$\sum_{i=-1}^{2} \delta_{\pi i}$	0.217	0.095	0.024	0.225	0.094	0.019
ϕ_{VXO}	−0.071	0.040	0.078	−0.068	0.040	0.095
ϕ_U	0.002	0.025	0.926	−0.030	0.064	0.635
N		123			123	
RMSE		0.241			0.240	
$\overline{R}^2$		0.321			0.322	
Greenspan-Bernanke sample: 18 August 1987 – 29 October 2008						
Intercept	0.050	0.160	0.755	0.064	0.167	0.701
γ_b	−0.065	0.018	0.000	−0.065	0.018	0.000
$\sum_{i=-1}^{2} \gamma_{yi}$	0.110	0.018	0.000	0.111	0.018	0.000
$\sum_{i=-1}^{2} \gamma_{\pi i}$	0.188	0.043	0.000	0.185	0.041	0.000
γ_{u0}	−0.085	0.025	0.001	−0.087	0.026	0.001
$\sum_{i=-1}^{2} \delta_{yi}$	0.026	0.030	0.400	0.025	0.030	0.416
$\sum_{i=-1}^{2} \delta_{\pi i}$	−0.050	0.066	0.448	−0.050	0.066	0.450
ϕ_{VXO}	−0.032	0.013	0.013	−0.032	0.012	0.010
ϕ_U	−0.002	0.017	0.904	0.009	0.039	0.818
N		171			171	
RMSE		0.154			0.154	
$\overline{R}^2$		0.521			0.522	

Note. The left panel presents estimates for our reaction function (8) with the output growth uncertainty measure: $U_m = U_{\pi m}$. The right panel presents estimates with the probability of being in a high-uncertainty regime given by equation (9): $U_m = F(U_{\pi m})$. The VXO and inflation uncertainty series are standardized on each subsample prior to estimation. Reported standard errors and p-values are robust to heteroscedasticity and autocorrelation, estimated with Bartlett kernel and data-driven bandwidth estimated with AR(1) model by maximum likelihood (Andrews, 1991). The sample dates indicate the first and last FOMC meeting in the sample.

These values are reasonable in terms of what Koop and Korobilis (2013) find to be optimal hyperparameters for a small monetary VAR (see footnote 17). The only result that is relatively sensitive to changes in the hyperparameters is the linear response to entropy uncertainty on the full sample. It is significant at the 5% level only for $\lambda = 1$ (the constant-parameter version of the TVP-VAR). However, the full-sample response to being in a high-uncertainty regime is significant at the 5% level across all hyperparameter values that we consider. The effect sizes vary between the 9 and 14 basis points, where the effect gets larger as λ approaches 1. The estimates for the Martins-Burns-Miller sample are consistent across hyperparameters, as are those for the Greenspan-Bernanke sample. The size of the response to output growth uncertainty on the latter sample varies between 7 and 10 basis points, where the largest effects correspond to $\lambda = 1$.

Second, we vary the parameter θ, which determines the shape of the probability function in equation (9). We focus on the regime estimates that use entropy uncertainty on the full sample and that use output growth uncertainty on the Greenspan-Bernanke sample. For values $\theta \in \{1, 5, 10, 25\}$, we find that the results are largely consistent. The estimated full-sample coefficients for the entropy-based probability variable lie between -0.33 and -0.099, with p-values between 0.020 and 0.033. The coefficients for the Greenspan-Bernanke sample (based on output growth uncertainty) lie between -0.15 and -0.069, with p-values between 0.006 and 0.033. The effect sizes get smaller as θ gets larger. We also consider the special case of a dummy that equals one when the uncertainty is above its median (as computed on the respective sample), and zero otherwise.[23] This case gives coefficients of -0.083 ($p = 0.043$) on the full sample, and -0.066 ($p = 0.012$) on the Greenspan-Bernanke sample.

Third, we exclude the Greenbook nowcast from the real-time vintages, meaning that we only use data up to and including the quarter before the meeting takes place. We calculate macroeconomic uncertainty using the posterior density of nowcasts for the quarter the meeting takes place, instead of using the density of forecasts for next quarter.

[23] This corresponds to the case $\theta \to \infty$, apart from the times when the uncertainty measure exactly equals the median, in which case the limit equals 1/2.

The most notable difference with the baseline results is that the full-sample estimated responses (both linear and regime) to entropy uncertainty are only significant at the 10% level. However, the response to being in a high-uncertainty regime, as calculated using output growth uncertainty, is still significant at the 5% level on the full sample. The other results are in line with our baseline estimates.

4. Conclusion

Using a new, Bayesian, real-time measure of macroeconomic uncertainty, we find for the period 1969 – 2008 that monetary policy responds to macroeconomic uncertainty with a significant decrease in the intended federal funds rate. Specifically, being in a high-uncertainty regime leads to a decrease in the intended funds rate of about 14 basis points.

We split the sample into subsamples before and after the period of non-borrowed reserves targeting, and zoom in on different components of macroeconomic uncertainty. These estimates also indicate that a specification with low- versus high-uncertainty regimes best captures the relationship between uncertainty and monetary policy. On the full sample, the effect of being in a high uncertainty regime also holds when measured by output growth uncertainty or inflation uncertainty. The results furthermore imply that the reaction function of the Fed changes over time. In particular, macroeconomic uncertainty only plays a significant role in the later subsample, covering Greenspan's and part of Bernanke's tenure as chairman. Being in a high-output-growth-uncertainty regime leads to a decrease in the intended funds rate of 9.1 basis points. We find no significant funds rate response to uncertainty in the period 1969 – 1979.

These responses to macroeconomic uncertainty are orthogonal to the effect of financial uncertainty, proxied by the VXO index. On the full 1969 – 2008 period, as well as on the later subsample, an increase in the VXO index also leads to a significant decrease in the intended funds rate.

Our measure could further be used to investigate whether it is optimal for monetary policy to respond to uncertainty. One approach would be to revisit Romer and Romer's (2004) analysis of monetary policy effectiveness, distinguishing between macroeconomic uncertainty regimes and taking into account the policy response to uncertainty. Such a study would be similar to the one by Falck et al. (2019) in the context of disagreement about inflation expectations. One could also use our new uncertainty measure to contribute to the stream of literature that looks at uncertainty and its impact at the macro level, which has taken off after the seminal study of Bloom (2009). If macroeconomic uncertainty plays a role in recessions, as some studies in this stream have suggested, it would make sense for monetary policy to respond accordingly.

References

Ahmed, N. A., Gokhale, D. V., 1989. Entropy expressions and their estimators for multivariate distributions. IEEE Transactions on Information Theory 35 (3), 688–692.

Andrews, D. W. K., 1991. Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. Econometrica 59 (3), 817–858.

Batra, R. N., Ullah, A., 1974. Competitive Firm and the Theory of Input Demand under Price Uncertainty. Journal of Political Economy 82 (3), 537–548.

Berger, J. O., Smith, L. A., 2019. On the Statistical Formalism of Uncertainty Quantification. Annual Review of Statistics and Its Application 6 (1), 433–460.

Bernanke, B. S., 1983. Irreversibility, Uncertainty, and Cyclical Investment. The Quarterly Journal of Economics 98 (1), 85–106.

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S. J., 2018. Really Uncertain Business Cycles. Econometrica 86 (3), 1031–1065.

Caggiano, G., Castelnuovo, E., Nodari, G., 2018. Risk management-driven policy rate gap. Economics Letters 171, 235–238.

Caldara, D., Fuentes-Albero, C., Gilchrist, S., Zakrajšek, E., 2016. The macroeconomic impact of financial and uncertainty shocks. European Economic Review 88, 185–207.

Coibion, O., 2012. Are the Effects of Monetary Policy Shocks Big or Small? American Economic Journal: Macroeconomics 4 (2), 1–32.

Coibion, O., Gorodnichenko, Y., 2011. Monetary Policy, Trend Inflation, and the Great Moderation: An Alternative Interpretation. American Economic Review 101 (1), 341–370.

Doan, T., Litterman, R., Sims, C., 1984. Forecasting and conditional projection using realistic prior distributions. Econometric Reviews 3 (1), 1–100.

Durbin, J., Koopman, S. J., 2012. Filtering, smoothing and forecasting. In: Time Series Analysis by State Space Methods: Second Edition. Oxford University Press.

Evans, C., Fisher, J., Gourio, F., Krane, S., 2016. Risk Management for Monetary Policy Near the Zero Lower Bound. Brookings Papers on Economic Activity 2015 (1), 141–219.

Falck, E., Hoffmann, M., Hürtgen, P., 2019. Disagreement about inflation expectations and monetary policy transmission. Journal of Monetary Economics.

Gnabo, J.-Y., Moccero, D. N., 2015. Risk management, nonlinearity and aggressiveness in monetary policy: The case of the US Fed. Journal of Banking & Finance 55, 281–294.

Greenspan, A., 2004. Risk and Uncertainty in Monetary Policy. American Economic Review 94 (2), 33–40.

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

Koop, G., Korobilis, D., 2013. Large time-varying parameter VARs. Journal of Econometrics 177 (2), 185–198.
Kording, K. P., 2014. Bayesian statistics: Relevant for the brain? Current Opinion in Neurobiology 25, 130–133.
Leland, H. E., 1968. Saving and Uncertainty: The Precautionary Demand for Saving. The Quarterly Journal of Economics 82 (3), 465–473.
Litterman, R. B., 1986. Forecasting with Bayesian Vector Autoregressions: Five Years of Experience. Journal of Business & Economic Statistics 4 (1), 25–38.
Milani, F., 2011. Expectation shocks and learning as drivers of the business cycle. The Economic Journal 121 (552), 379–401.
Mumtaz, H., Theodoridis, K., 2019. Dynamic effects of monetary policy shocks on macroeconomic volatility. Journal of Monetary Economics.
Orlik, A., Veldkamp, L., 2014. Understanding Uncertainty Shocks and the Role of Black Swans. Working Paper 20445, National Bureau of Economic Research.
Orphanides, A., 2001. Monetary Policy Rules Based on Real-Time Data. American Economic Review 91 (4), 964–985.
Panetta, F., 2020. The price of uncertainty and uncertainty about prices: Monetary policy in the post-COVID-19 economy.
Rich, R., Tracy, J., 2010. The Relationships among Expected Inflation, Disagreement, and Uncertainty: Evidence from Matched Point and Density Forecasts. The Review of Economics and Statistics 92 (1), 200–207.
Romer, C. D., Romer, D. H., 2004. A New Measure of Monetary Shocks: Derivation and Implications. American Economic Review 94 (4), 1055–1084.
Smets, F., Wouters, R., 2007. Shocks and frictions in US business cycles: A Bayesian DSGE approach. American Economic Review 97 (3), 586–606.
Stock, J. H., Watson, M. W., 2002. Macroeconomic Forecasting Using Diffusion Indexes. Journal of Business & Economic Statistics 20 (2), 147–162.
Viscusi, W. K., 1985. Are Individuals Bayesian Decision Makers? American Economic Review 75 (2), 381–385.
Wieland, J. F., Yang, M.-J., 2020. Financial Dampening. Journal of Money, Credit and Banking 52 (1), 79–113.
Yu, A. J., 2007. Adaptive Behavior: Humans Act as Bayesian Learners. Current Biology 17 (22), R977–R980.

Appendix A. Additional figures

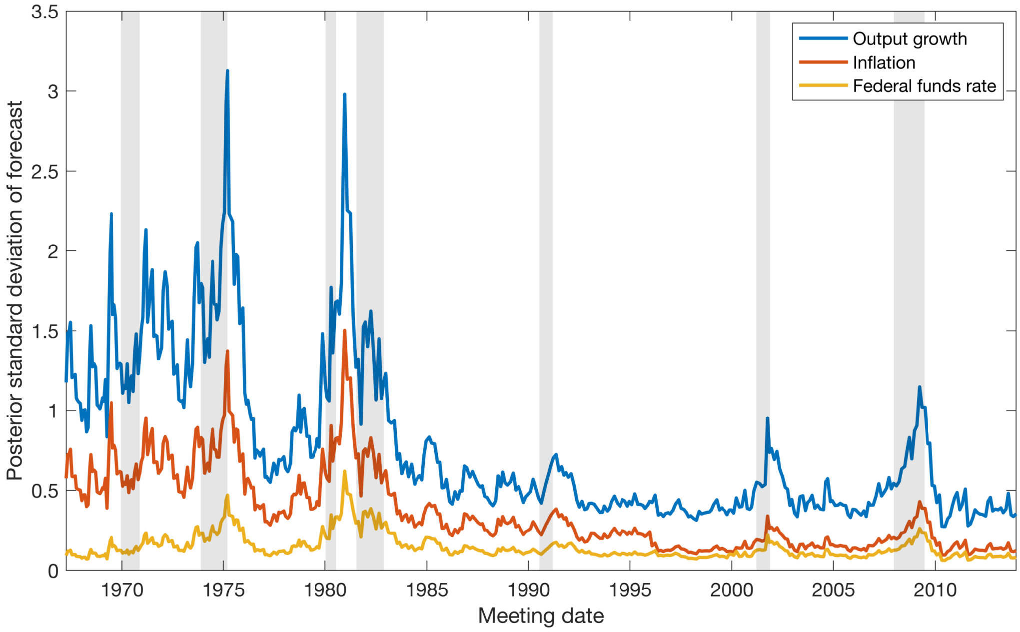

Figure A.4: Uncertainty related to one-quarter-ahead forecasts of output growth (U_{ym}), inflation ($U_{\pi m}$), and the federal funds rate (U_{im}). The measures are computed as the square root of the corresponding diagonal element in the covariance matrix of the posterior density of forecasts ($\widetilde{R}_{m,T_m+1}$). The grey bars indicate NBER recessions.

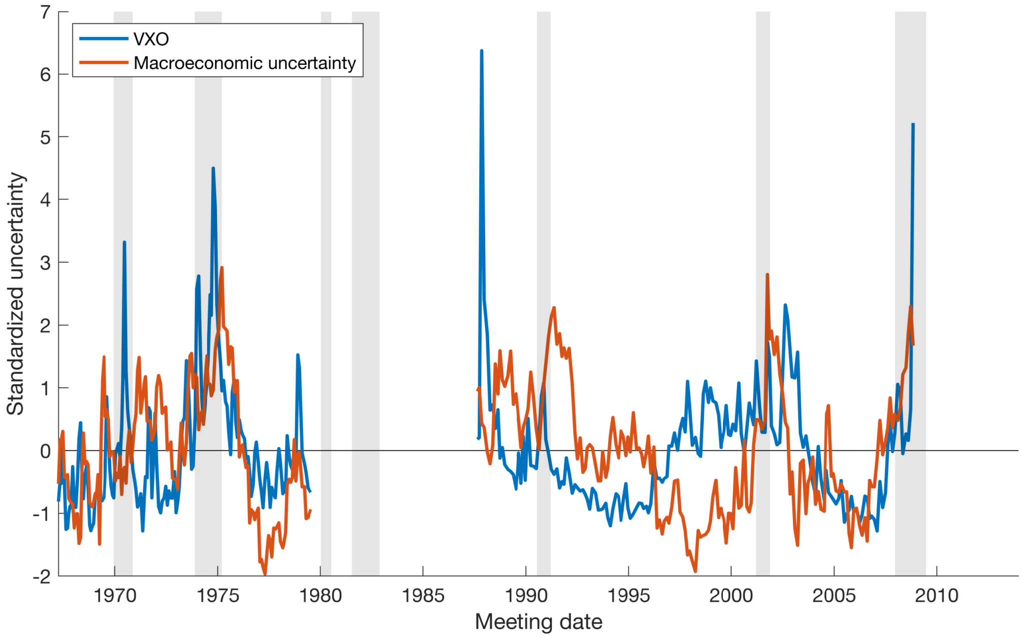

Figure A.5: Financial uncertainty proxy (VXO index) and entropy measure of macroeconomic uncertainty on Martins-Burns-Miller (1969 – 1979) and Greenspan-Bernanke (1987 – 2008) samples. Both series are standardized to have zero mean and unit standard deviation on the respective subsamples. The grey bars indicate NBER recessions.

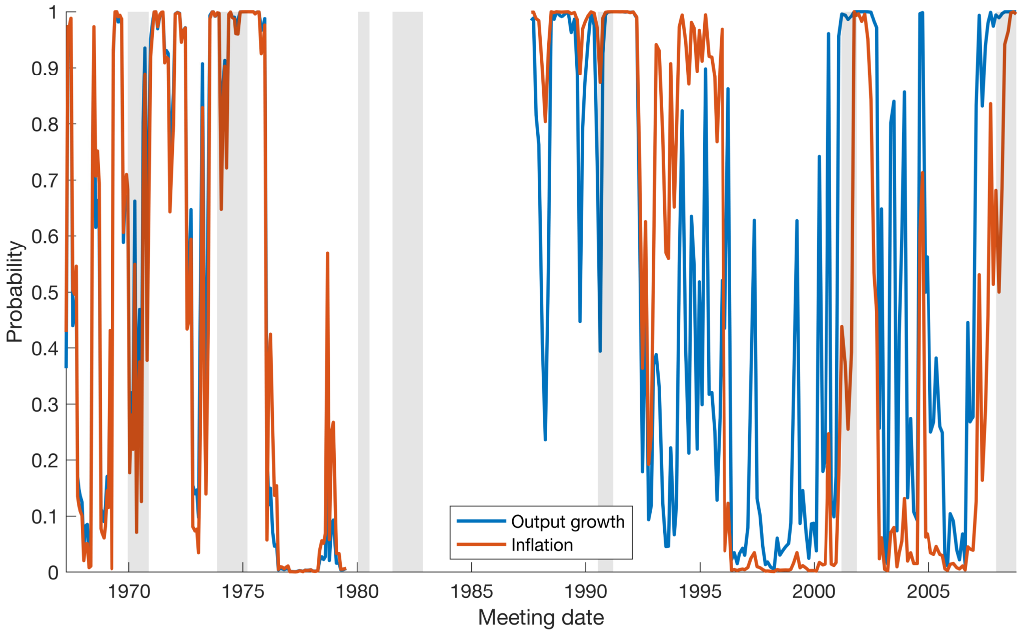

Figure A.6: Probability of being in a high-uncertainty regime, as defined in terms of output growth uncertainty (blue) and inflation uncertainty (red). The probabilities are calculated for the Martins-Burns-Miller (1969 – 1979) and Greenspan-Bernanke (1987 – 2008) samples separately, that is, using the subsample values for the median and standard deviation in (9). The grey bars indicate NBER recessions.