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# Monetary Policy Uncertainty and Inflation Expectations\*

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## Abstract

Do inflation expectations react to changes in the volatility of monetary policy? They have, but only until the global financial crisis. This paper investigates whether increasing the dispersion of monetary policy shocks, which is interpreted as elevated uncertainty surrounding monetary policy, affects the inflation expectation formation process. Based on US data since the 1980s and a stochastic volatility-in-mean structural VAR model, we find that monetary policy uncertainty reduces both inflation expectations and inflation. However, after the Great Recession this link has disappeared, even when controlling for the Zero Lower Bound.

## I. Introduction

“Inflation targeting, at least in its best-practice form, consists of two parts: a policy framework of constrained discretion and a communication strategy that attempts to focus expectations and explain the policy framework to the public. Together, these two elements promote both price stability and well-anchored inflation expectations.” - Bernanke (2003)

The seminal contribution of Lucas (1976) has highlighted the importance of expectations for the effectiveness of economic policy. Inflation expectations play a key role for wage and price setting (Clarida, Gali and Gertler, 2000; Svensson, 2000). As a consequence, over the past 40 years, the conduct of monetary policy has markedly changed with increasing emphasis on communication and transparency (Bernanke and Woodford, 1997; Blinder *et al.*, 2008). For example, in 1994, the Federal Open Market

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Committee (FOMC) began releasing statements regarding their monetary policy decisions, and in 2012, the US Federal Reserve (FED) officially adopted an inflation target of 2%. Since the global financial crisis, the main monetary policy instrument – the federal funds rate (FED funds) – has been constrained by the zero lower bound (ZLB). Recent literature has looked at the relevance of the ZLB in light of unconventional monetary policy. While Swanson and Williams (2014) and Debortoli, Galí and Gambetti (2019) suggest that the ZLB has not been particularly binding due to the effectiveness of forward guidance, Ikeda *et al.* (2020) find strong evidence that the constraint has been empirically relevant in the United States and Japan. Therefore, managing inflation expectations has become even more important for the transmission mechanism of monetary policy.

The effectiveness of monetary policy relies in part on the ability of economic agents to anticipate monetary policy movements. Consequently, a large part of monetary economics has dealt with studying the effects of unanticipated monetary policy shocks. However, a growing literature has also considered a different take on the relationship – how does unpredictability of monetary policy affect the economy? This is referred to monetary policy uncertainty (MPU). Although MPU has been studied not least due to its relevance for central bank credibility (e.g., Stulz, 1986; Neely, 2005; Swanson, 2006), it has gained considerable emphasis since the global financial crisis, along with other types of uncertainty.<sup>1</sup>

A commonality across the empirical MPU literature findings is that, irrespective of the chosen proxy, an increase in monetary policy uncertainty suppresses economic activity, increases unemployment, and leads to a decline in prices. The theoretical underpinnings of these findings suggest that the consumption channel plays an important role – risk-averse agents hold back consumption, which creates a decline in demand (Mumtaz and Zanetti, 2013). Essentially, MPU shocks are a materialization of negative demand shocks and hence propagate through the expectations of economic agents. However, the focus of the inflation expectations literature has mostly been on the effects of monetary policy shocks, not on MPU shocks (Leduc, Sill and Stark, 2007; Canova and Gambetti, 2009; Leduc and Sill, 2013). Not controlling for the uncertainty component might overlook an important aspect in the inflation expectation formation process. Hence, in this article, we investigate empirically the link between MPU and inflation expectations.

To do so, an important question is how to measure MPU. MPU has been typically defined as some function of the ability of economic agents to forecast monetary policy instruments, that is, interest rates. One example is measuring surprises to agents via options and yield curve movements (Swanson, 2006; Bauer, 2012; Chang and Feunou, 2014). More recently, natural language processing (less formally text analysis) has also been employed to create MPU proxies, either through newspaper-based articles (Baker, Bloom and Davis, 2016; Husted *et al.*, 2020) or the FOMC meetings (Hansen *et al.*, 2018).

A further example, popular in structural models, is to postulate specific distributional assumptions on key target central bank variables, either the money supply (Stulz, 1986) or, more recently, the interest rates (Mumtaz and Zanetti, 2013; Creal and Wu, 2017;

<sup>1</sup> See, for example, Bauer (2012); Kang, Lee and Ratti (2014); Chang and Feunou (2014); Mumtaz and Zanetti (2013); Istrefi and Piloiu (2014); Mumtaz and Theodoridis (2015); Sinha (2016); Creal and Wu (2017); Kurov and Stan (2018); Hansen, McMahon and Prat (2018); Istrefi and Mouabbi (2018); Husted, Rogers and Sun (2020); Bauer, Lakdawala and Mueller (2019); Alessandri and Mumtaz (2019).

Alessandri and Mumtaz, 2019). In these contributions, MPU is modelled in the second-order moment, that is, the variance of the central bank policy instrument. An increase in MPU is then defined as an increase in the variance of monetary policy shocks. The hypothesis is that larger monetary policy shocks worsen forecasts of economic agents and thus make it harder to anticipate the correct movements of the target variable.

We incorporate MPU following the latter approach and estimate a structural VAR (SVAR) with stochastic volatility-in-mean to study the interaction between MPU and inflation expectations. Capturing the joint dynamics of inflation, inflation expectations, and economic activity is natural in the framework of SVARs. Our work is related to the growing literature, which focuses on the effects of economic policy uncertainty on the economy (Bloom, 2009; Mumtaz and Zanetti, 2013; Baker *et al.*, 2016; Bachmann *et al.*, 2019). We focus specifically on MPU, departing from recent works that look at the macroeconomic effects of changes in broader measures of uncertainty (Istrefi and Piloju, 2014; Fernández-Villaverde *et al.*, 2015).

In a sample spanning from 1982 to 2019, we find that, on average, in the United States, short-run inflation expectations do indeed decline following an MPU shock, although not in the same magnitude as inflation, suggesting that expectations are rigid. On the other hand, long-run inflation expectations, which are typically found not to react to monetary policy shocks (Canova and Gambetti, 2009), do not seem to be affected by MPU shocks. Furthermore, we show that the relationship between MPU and inflation expectations has not remained stable over time. Since the Great Recession, short-run inflation expectations have not reacted to MPU shocks, while inflation has. These findings suggest that, while MPU might have been important in the past for the expectation formation process, this has not been the case over the past decade, even when we control for the ZLB.

The remainder of this paper is structured as follows. The next section lays out the methodology used in this article. Section III is devoted to the summary of the data set. Sections IV and V discuss the results and Section VI concludes.

## II. Modelling monetary policy uncertainty

This section presents the adopted empirical strategy for estimating the effects of uncertainty on inflation expectations. We follow the approach of modelling MPU as a second-moment shock to the monetary policy instrument (e.g. Stulz, 1986). We adopt the framework of Mumtaz and Zanetti (2013), estimating a stochastic volatility-in-mean SVAR, which has already been employed for the analysis of MPU on economic activity (Mumtaz and Zanetti, 2013; Alessandri and Mumtaz, 2019). In this set-up, MPU is captured by the time-varying variance of monetary policy shocks, which are extracted from the central bank interest rate series. In the spirit of Swanson (2006), an increase in the variance lowers the ability of economic agents to forecast interest rates.<sup>2</sup> For the remainder of this paper, we will use the terms uncertainty and volatility interchangeably.<sup>3</sup>

<sup>2</sup>This definition of uncertainty is popular in the literature. For example Jurado, Ludvigson and Ng (2015) frame financial and macroeconomic uncertainty as the variance of a time-varying forecast error from a dynamic factor model.

<sup>3</sup>We do acknowledge that there is a difference between implied and realized volatility. Our results draw on a measure based on realized interest rate volatility. See Bachmann *et al.* (2019) for a discussion on the subject.

An appealing property of the model is that it constitutes a one-step procedure in modelling uncertainty, that is, both the coefficients and the uncertainty measure are estimated jointly from the data, thus providing an important feedback loop. This is in contrast to a model where the proxy is constructed first from an exogenous source and then put into a model as it avoids potential measurement errors.<sup>4</sup>

### SVAR with stochastic volatility in-mean

The framework of Mumtaz and Zanetti (2013) may be summarized by the following key equations. The VAR is given by:

$$Z_t = c + \sum_{j=1}^P \beta_j Z_{t-j} + \sum_{m=0}^M \gamma_m \tilde{h}_{t-m} + \Omega_t^{1/2} e_t, \quad e_t \sim N(0, I_K), \quad (1)$$

where  $Z_t$  is a vector of endogenous variables of dimension  $K \times 1$  and the vector  $\tilde{h}_t = [h_{1t}, \dots, h_{Kt}]'$  contains the log volatilities of the  $K$  structural shocks. The shocks are extracted from the reduced-form variance–covariance matrix  $\Omega_t$  using an orthogonal decomposition  $\Omega_t = A^{-1} H_t A^{-1'}$  and  $A^{-1}$  collects the contemporaneous relationships between the variable.  $H_t$  is a diagonal matrix with  $\exp\{\tilde{h}_t\}$  on its diagonal. The processes for the log volatilities are assumed to be autoregressive of first order, of the form:

$$\tilde{h}_t = \Theta \tilde{h}_{t-1} + \eta_t, \quad \eta_t \sim N(0, \xi), \quad \mathbb{E}(e_t \eta_t) = 0, \quad (2)$$

such that  $\Theta$  is a  $K \times K$  diagonal matrix and  $\eta_t = [\eta_{1t}, \dots, \eta_{Kt}]'$ . Furthermore we assume that the first- and second-moment shocks are uncorrelated.<sup>5</sup>

Let  $r_t$  denote the monetary policy instrument in the vector of endogenous variables,  $Z_t$ . Then  $h_{rt}$  is our MPU measure, which affects the levels of the rest of the variables through the  $\gamma$  coefficients. The innovations  $\eta_t$  in equation 2 are the uncertainty shocks in our framework with  $\eta_{rt}$  being the MPU shock. An increase in  $\eta_{rt}$  means that the monetary policy instrument may take a wider range of values as the shock dispersion increases.

### Model with time-varying coefficients

This model captures the average response to uncertainty shocks over the full sample. Throughout the last 40 years, the US economy has experienced significant events, from the great moderation to the global financial crisis, which could have contributed to changes between the relationships of economic variables. Furthermore, it has been shown that inflation expectations depend on the own experience of the economic agents, that is, people who lived through periods of high inflation expect, on average, higher

<sup>4</sup>This is not to say that one-step approaches do not come without drawbacks. For example, model misspecification would undermine the generated regressors (the uncertainty indicators). The choice of one- versus two-step approaches presents a trade-off between internal consistency and robustness to misspecification. For discussion of one-step versus two-step estimations of uncertainty indices, see Bianchi, Kung and Tirsikh (2018).

<sup>5</sup>This assumption eases the computational burden but it may be relaxed, as, for example, in Alessandri and Mumtaz (2019).

inflation (Malmendier and Nagel, 2016; Draeger and Lamla, 2018). Finally, a large part of the literature on uncertainty has shown that the relationship between uncertainty and economic activity might be nonlinear (Caggiano, Castelnuevo and Groshenny, 2014; Alessandri and Mumtaz, 2019), and specifically monetary policy shocks (Castelnuevo and Pellegrino, 2018). Therefore, we deem it important to investigate whether the inflation expectations formation process has evolved over time and how the link between MPU and expectations has behaved throughout different periods.

To do so, we estimate an extended version of the model by allowing the coefficients to change over time, along the lines of Primiceri (2005) and Mumtaz and Theodoridis (2020). Thus, our analysis falls in a broad class of studies analysing the time variation of economic shocks (Benati and Surico, 2008; Mumtaz and Zanetti, 2015; Liu *et al.*, 2019).

We introduce time-varying parameters (TVP) for the coefficients of the estimated VAR,  $\beta$  and  $\gamma$ , thus capturing potential changes among the economic variables and how uncertainty is perceived over time. Equation (1) is modified to incorporate time variation in the following way:

$$Z_t = c_t + \sum_{j=1}^P \beta_{j,t} Z_{t-j} + \sum_{m=0}^M \gamma_{m,t} \tilde{h}_{t-m} + \Omega_t^{1/2} e_t, \quad e_t \sim N(0, I_K), \quad (3)$$

We postulate a random walk process for the coefficients:

$$B_t = B_{t-1} + v_t, \quad v_t \sim N(0, Q), \quad (4)$$

where  $B_t = [\beta_t, \gamma_t]'$  and  $Q$  governs the amount of time variation in the parameters.

### Estimation strategy

Due to the presence of the volatility terms in equation (1), the conventional maximum likelihood approach is not applicable. The model is estimated via Bayesian methods with Gibbs sampling, that is, drawing the parameters iteratively from their conditional distributions.

The estimation procedure for the TVP and no-TVP specification is mostly the same. The parameters may be divided into several blocks based on their distributional assumptions. The reduced-form coefficients  $B = [\beta, \gamma]$ , and  $B_t = [\beta_t, \gamma_t]$  in the TVP case, respectively, along with the  $Q$  matrix, the stochastic volatility block  $\mathcal{H} = \{H_1, \dots, H_T\}$ , where  $H$  is a diagonal matrix containing the  $\tilde{h}$ , the parameters  $\Theta$  in the equation, and the contemporaneous responses  $A$ .

In order to simplify the exposition, we introduce notation  $\Psi = \{A, B, Q, \mathcal{H}, \Theta\}$ , which collects the different blocks of parameters. Let  $\Psi^{-i}$  denote the exclusion of the  $i$ th block such that  $\Psi^{-B} = \{A, Q, \mathcal{H}, \Theta\}$ .

To conduct inference, we draw the  $i$ th block from the conditional probability distribution  $p(i|\Psi^{-i})$ , which is derived as a function of a conjugate prior distribution  $\bar{p}(i)$ . The prior for the reduced-form coefficients  $B$  and  $\tilde{h}$  is based on a GLS estimation on a training sample. For arbitrary starting values, the estimation proceeds in the following iterative procedure:

1. Conditional on  $\mathcal{H}$ ,  $A$  may be drawn as a linear regression from  $p(A|\Psi^{-A})$ , given the form in equation (2) in conjunction with the algorithm of Cogley and Sargent (2005).
2. The reduced-form parameters,  $B$ , are obtained from a linear regression with heteroskedasticity and may be estimated via GLS. Following Carter and Kohn (1994), we introduce stochastic volatility via a matrix  $Q$ , employ the Kalman filter for  $t = 1, \dots, T$  to get  $\beta_{T|T}$  and  $\gamma_{T|T}$  and draw the parameters from  $p(\beta_{T|T}, \gamma_{T|T}|Q, \Psi^{-B, -Q})$ .
3. Conditional on the draws for  $B$ ,  $Q$  may be drawn from an inverse Wishart distribution.
4. For the stochastic volatility estimation, we follow Cogley and Sargent (2005), where the draws for  $\mathcal{H}$  may be obtained using a Metropolis–Hastings algorithm conditional on the model parameters.

The only notable difference when estimating the TVP specification is that the time variation in the model is governed by the process given in (4), for which the specification of  $Q$  is of importance. The constant parameter version is nested here for extremely low values of  $Q$ , while high values permit larger jumps in the parameters. Given that the random walk process introduces potential explosiveness, exceptionally high values could make inference impossible. To deal with this issue, in the seminal contribution of Primiceri (2005),  $Q$  is scaled a-priori via an additional parameter,  $k_Q$ . This choice is of specific importance. Our goal is to find the appropriate amount of time variation without imposing overly strong restrictions on the parameters' movement nor running into estimation difficulties. In Primiceri (2005)  $k_Q$  is chosen using a grid-search with the aim to maximize the marginal likelihood of the model with an optimal value of  $k_Q = 0.01$  for US data. However, our data set is monthly, hence there is no guarantee that this is an appropriate choice for our application.

We follow recent advancements in Bayesian computation of TVP models and treat  $k_Q$  as a hyperparameter to be estimated from the data as in Amir-Ahmadi, Matthes and Wang (2018) by using a random walk Metropolis–Hastings algorithm with an inverse gamma distribution as a prior. We plot the posterior densities of  $k_Q$  in the Appendix, Section A. The corresponding estimates of  $k_Q$  lead to a median value of 0.063. We use this median of the posterior density of  $k_Q$  to calculate the impulse response functions of the TVP model.

### III. Data and estimation

Our data set consists of five macroeconomic variables: the civilian unemployment rate; the long-run and short-run inflation expectations; the consumer price index (CPI) inflation rate; and the monetary policy rate. Given that our measure of uncertainty relies on the volatility of the variables, the ZLB presents a significant issue. For this reason, we choose the shadow short rate (SSR) as a proxy for the main monetary policy instrument. Thus, we also capture the unconventional monetary policy measures, which are reflected in the SSR. For robustness, we also consider the model with federal funds rate (FED Funds).

The key variables of interest in our study are the inflation expectations. Therefore, we use the proxies developed in Haubrich, Pennacchi and Ritchken (2012), where expectations are extracted using a term-structure model of the interest rates. These data



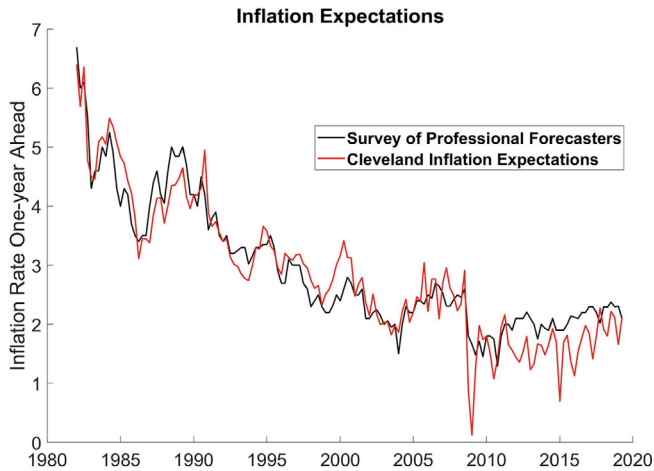


Figure 1. One-year ahead inflation expectations from the Survey of Professional Forecasters and from Haubrich *et al.* (2012). Quarterly frequency.

Source: Federal Reserve Bank of Philadelphia and the Federal Reserve Bank of Cleveland

have several appealing properties. First and foremost, the financial sector is a crucial channel for the expectations of economic agents; thus, proxies based on interest rate data should provide timely adjustment of inflation expectations. Second, the expectation measures are available both for short and long term (1 year ahead and 5 years ahead), starting in 1982. In contrast, the long-run expectations of the Survey of Professional Forecasters (SPF) only starts in 2005. Third, the data are at a monthly frequency. This increases the degrees of freedom in our highly parameterized nonlinear model. Finally, the term-structure model accounts for liquidity and risk premia. This is an important difference from other measures of inflation expectations based on interest rate data, like the treasury inflation-protected securities (TIPS) that do not account for such premia. However, this comes at a cost, as the proxy is an outcome of a term-structure model, hence carries model uncertainty, which cannot be incorporated into the analysis. For example, misspecification could lead to an over- or underestimation of our probability intervals – a different inflation expectations measure might exhibit different dynamics.<sup>6</sup> Figure 1, plots the quarterly aggregated measure from Haubrich *et al.* (2012) versus the SPF.

The unemployment rate, CPI inflation, and the FED Funds were obtained from the Federal Reserve Bank of St. Louis Database. The shadow short rate (SSR) was obtained from Wu and Xia (2016).<sup>7</sup> Finally, we use the estimations from Haubrich *et al.* (2012) for the long-run and short-run inflation expectations taken from the Federal Reserve Bank of Cleveland. The sample ranges from January 1982 to June 2019.

<sup>6</sup>We have also explored an alternative specification, where the 1-year ahead SPF data have been interpolated using a mixed frequency VAR as in Schorfheide and Song (2015). We find that our conclusions remain the same. Results are available upon request.

<sup>7</sup>Our findings are robust to the choice of SSR as we have also considered the alternative by Leo Krippner.



## Statistical identification and inference

To determine the optimal number of lags in equation (1), we employed information criteria tests on the reduced-form specification without stochastic volatility terms. The proposed lag lengths are 2 and 12 for BIC and AIC, respectively. We choose two lags for the baseline specification, to prevent parameter proliferation in the time-varying case. In the constant parameter case, we also test 12 lags and find that the results are robust to that specification.<sup>8</sup>

Following the estimation strategy from Section II, we initialize the model estimation using the first 10 years as training sample. Thus, after accounting for the lag length, the effective sample begins in March 1992. We use 1,00,000 iterations of the Gibbs sampler, of which the first 95,000 are discarded as burn-in. We test for the convergence of the chain with standard procedures and discuss the results in Appendix D.

To identify the monetary policy shocks, we use Cholesky decomposition with a lower triangular matrix, where following the sticky-information literature (Castelnuovo and Surico, 2010), we order inflation expectations above inflation. Thus, we assume that they do not respond within the same month to new information regarding the interest rates or inflation.<sup>9</sup> Apart from that, we follow standard ordering of unemployment, inflation, and the monetary policy rate (Christiano, Eichenbaum and Evans, 1999). Nevertheless, we test our results to different specifications and find that they are consistent with the baseline. This is due to the fact that we are interested in the impulse responses following a shock to the stochastic volatilities,  $\eta$ . Thus, a major determinant of the effects of uncertainty shocks are the  $\gamma$  coefficients, and variable ordering plays a secondary role. This holds as long as the estimated stochastic volatilities  $h$  remain the same across orderings. This is an advantage of the framework over set-ups where the uncertainty measure is an additional series whose level is shocked (e.g. Istrefi and Piloju, 2014).

## IV. Estimated uncertainty measures

Figure 2 plots the MPU series implied by the two models, the TVP and the constant parameter specification, respectively, as well as an array of other popular uncertainty indicators from the literature. The measures from the two models are highly similar, with the constant parameter specification giving a bit more weight to the MPU at the height of the financial crisis as well as during 2013 – the year of the “taper tantrum”. Other than that, MPU is estimated to have been particularly high during the early 90s and following the events of the dot-com bubble. These dynamics mirror closely the estimated monetary policy volatility of Mumtaz and Zanetti (2013), whose sample ends in 2010Q4.

On the top right of Figure 2, the model implied measure is plotted against the MPU index from Baker *et al.* (2016) and Husted *et al.* (2020). All time series have been standardized to facilitate comparison. The latter two are based on newspaper data and are much more volatile, compared with the model estimate. Apart from the differences in smoothness, the three series appear to follow similar dynamics throughout the 1990s. However, since the early 2000s, there are notable differences. The model implies that

<sup>8</sup>The results are available in the Appendix.

<sup>9</sup>This has been found to be true for SPF data, see Coibion and Gorodnichenko (2015).

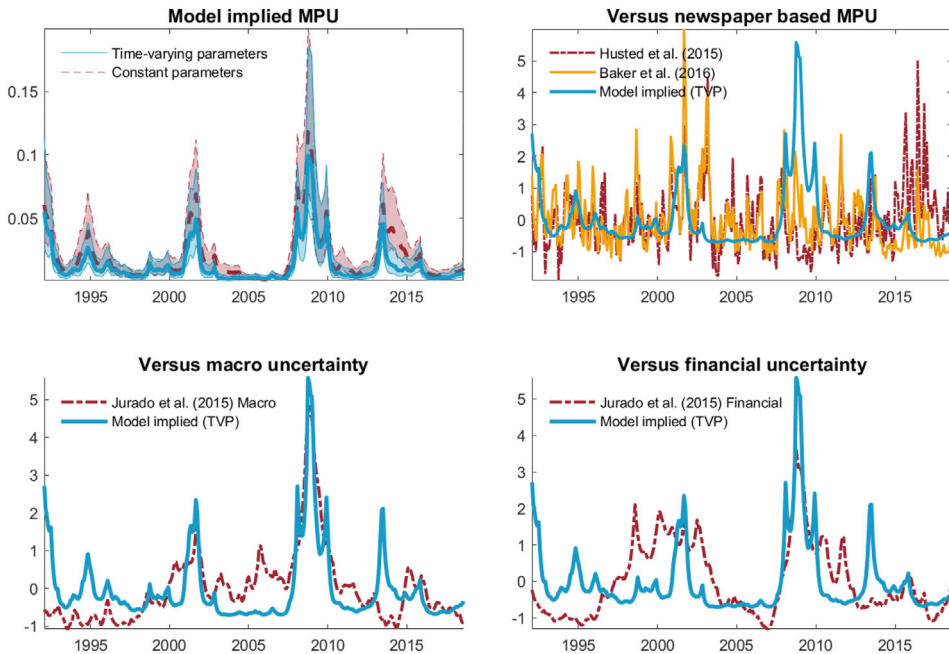


Figure 2. Measures of monetary policy uncertainty. Top left: estimates from the time-varying parameter (TVP) and constant parameter models with probability intervals (shaded). Top right: Model implied MPU versus the indices MPU indices from Baker *et al.* (2016) and Husted *et al.* (2020), standardized. Bottom left: Macro uncertainty from Jurado *et al.* (2015), standardized. Bottom right: financial uncertainty from Jurado *et al.* (2015), standardized

the highest peak of monetary policy volatility was surrounding the global financial crisis. The measure of Baker *et al.* (2016) – during the dot-com bubble and its aftermath, while the index of Husted *et al.* (2020) suggests that MPU was highest throughout the first years of the Trump administration.<sup>10</sup> The model estimate is by construction smoother; its dynamics are given by the autoregressive process in equation (2). It is also based on the estimated stochastic volatility of the monetary policy shocks identified using our SVAR, hence tightly related to the underlying SSR series and our identification assumptions.

Since economic shocks are by assumption unforecastable, the measure of Mumtaz and Zanetti (2013) is in spirit much closer to the approach taken by Jurado *et al.* (2015) where uncertainty is related to the second moments of a forecast distribution. We plot both macroeconomic and financial uncertainty based on Jurado *et al.* (2015) in the bottom panels of Figure 2. While all three measures display elevated uncertainty surrounding the global financial crisis, there appear to be notable differences in the other periods. Macro uncertainty displays lower but more prolonged peaks around the turn of the millennium and has even fallen during the ‘taper tantrum’ periods. Similarly, financial uncertainty also does not fluctuate after the financial crisis and on average appears to follow two long

<sup>10</sup>This is valid for our data span, which cuts short right before the index of Husted *et al.* (2020) reaches its historical maximum in August 2019 of 407 (long-run mean 110).

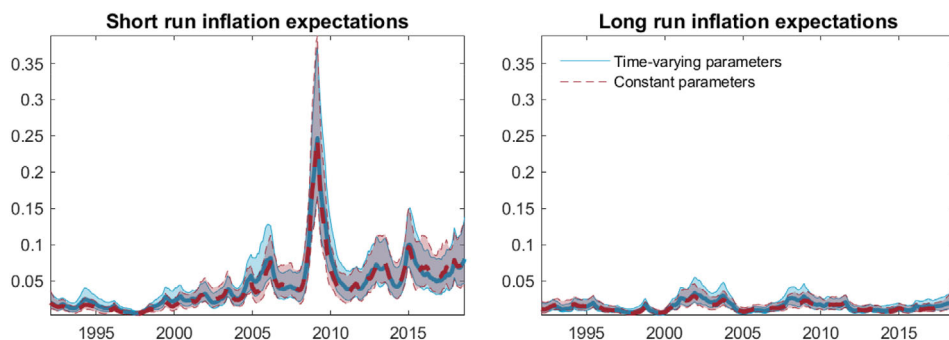


Figure 3. Measures of inflation expectations uncertainty from a time-varying parameter model and a constant coefficients specification. Median responses (solid and dashed line) and 68% probability intervals (shaded area)

cycles throughout the sample as opposed to MPU, which is estimated to have peaked shortly and only during specific events.<sup>11</sup>

Next, we report the volatility of the shocks to short- and long-run inflation expectations, which could be interpreted as uncertainty surrounding the inflation expectations. They are plotted in Figure 3 for each specification. The estimates are overlapping almost perfectly. Notably, long-run inflation expectations display a low and stable level of uncertainty, while short-run inflation expectations uncertainty increased during the Great Recession and remained elevated compared with the period before the 2008 crisis.<sup>12</sup> Long-run inflation expectations appear to be well anchored as their uncertainty level does not fluctuate even through dramatic events such as the global financial crisis. These estimates may also be seen through the lens of central bank credibility. Constant uncertainty surrounding the long-run expectations suggests trust in the monetary authority – a crucial condition for an efficient transmission of monetary policy. These findings are in line with the inflation gap literature that establishes low volatility of trend inflation (Cogley and Sbordone, 2008; Cogley, Primiceri and Sargent, 2010; Coibion and Gorodnichenko, 2011). However, long-run interest rates have been shown to respond to economic news (Guerkaynak, Sack and Swanson, 2005), which suggests that higher volatility of long-run inflation expectations could also be expected. The model, however, recovers the large volatility swings in the short-run inflation expectations only. Given the similarity between the two series, this raises the question whether the model always recovers the true peaks in the volatilities.

To test this hypothesis, we conduct a Monte Carlo exercise using artificially generated data. First, we generate data from a model in which short-run inflation expectations volatility  $h_{SR,t}$  for  $t = 1, \dots, T$  is extremely low, while long-run inflation expectations volatility is high. Then we estimate the model on that data set to see whether it would recover the volatility series correctly. We mirror this set-up with artificially generated data where the opposite is true; in the data generating process, short-run inflation expectations

<sup>11</sup>We control for financial uncertainty by extending our model with the returns from Standard and Poors' Index. We compare the estimated financial uncertainty from that model and report that it matches the Jurado et al (2015) measure much more closely. See Appendix C

<sup>12</sup>The estimated volatilities in the model with FED Funds are almost identical to the ones obtained with the SSR. Estimates are shown in the Appendix, Figure A2 and A3.

volatility is high and long run is low. We generate the data 200 times, 100 for each set-up and estimate correspondingly 200 times the model on the artificial data set. We find that in both cases the model correctly attributes the volatility to the correct scenario. Further details as well as a plot of the estimates may be found in Appendix, Section B.

## V. The effects of monetary policy uncertainty shocks

Next, we will examine the responses of the variables to a one standard deviation MPU shock. Overall, an MPU shock manifests as a negative demand shock, as documented by Mumtaz and Zanetti (2013) and Alessandri and Mumtaz (2019). Namely, an increase in MPU leads to a contraction of the real sector due to risk aversion and consumption smoothing behaviour and a decline in economic output (Mumtaz and Zanetti, 2013), as well as a fall in prices and the interest rate. With our monthly data set, we observe the same effects, unemployment increases while inflation and interest rates decline. However, when we allow for gradual evolution of the relationships between the variables, we find interesting developments, especially in relation to inflation expectations.

A concise way to highlight the time variation in the responses is to show the average responses of the model variables to an MPU shock during four different periods: (i) 1993 as the first full year of impulse responses after accounting for the training sample and the lag values; (ii) 2003 as a boom period after the recovery of the dot-com crash; (iii) 2008 to look to the effects during the Great Recession; and (iv) 2018 the last full year of estimates. We do this on Figures 4 through 8. For comparison, we also plot the responses from the constant parameter model, which by construction would be identical over the chosen periods.

Figure 4 shows the response of long-run inflation expectations to a monetary policy uncertainty shock. We find that with the exception of the beginning of the sample, the response of long-run inflation expectations is close to zero. The 68% probability intervals bands suggest that this response is not different from zero for the remaining part of the sample. The median response has evolved from slightly negative towards showing no link to reacting to monetary policy uncertainty. The constant parameter specification also captures a negative median response of the long-run inflation expectations, naturally with a tighter probability intervals due to the higher degrees of freedom. These findings are of particular interest because long-run inflation expectations are associated with the level of credibility the central bank maintains. This is especially important for monetary policy effectiveness in a context where forward guidance and other unconventional measures have been implemented. Along with the estimated low long-run volatility, these results reinforce the notion that long-run inflation expectations are well anchored.

Short-run inflation expectations, depicted in Figure 5, respond somewhat differently. The constant parameter model shows a negative response with the zero line falling outside of the probability intervals, in contrast to the long-run expectations case. In the TVP version, we see that these findings are driven primarily by the response of the short-run expectations throughout the first half of the sample. The median response of the TVP case (solid lines) lies below the constant parameter case (dashed lines) in 1993 and 2003, while it is less negative after the global financial crisis. Correspondingly

the 68% error bands show a decline in the short-run inflation expectations not only in the beginning of the sample, as long-run expectations do, but also before the financial crisis. After the beginning of the Great Recession, the negative response to MPU shocks has dissipated, indicating a distinct pre and postfinancial crisis dynamics of inflation expectations.

Next, we look at the response of inflation, shown in Figure 6, which is also negative. It is, however, different than the response of inflation expectations in Figures 4 and 5 in several key aspects. First, both the TVP and no-TVP model suggest a median estimated (including the error bands) outside of the zero line throughout almost the entire sample with the exception of the very last periods – inflation declines following an MPU shock. Given the lack of a strong response of both expectations series after the financial crisis, it appears that the transmission mechanism is not through the expectations channel. Second, the response of inflation has always been several magnitudes stronger than that of inflation expectations, indicative of a rigidity in the expectation formation process when it comes to MPU shocks. This is in contrast to the dynamics following an uncertainty shock to the real variable, unemployment, which is also a negative demand shock. In that case, all three variables react in a similar magnitude (See Appendix C).

To highlight these points, we present an alternative view of the MPU effects in Figure 7. It contains a cross section of the median responses of inflation and inflation expectations at specific horizons following an MPU shock – from 12 to 60 months ahead. The figure

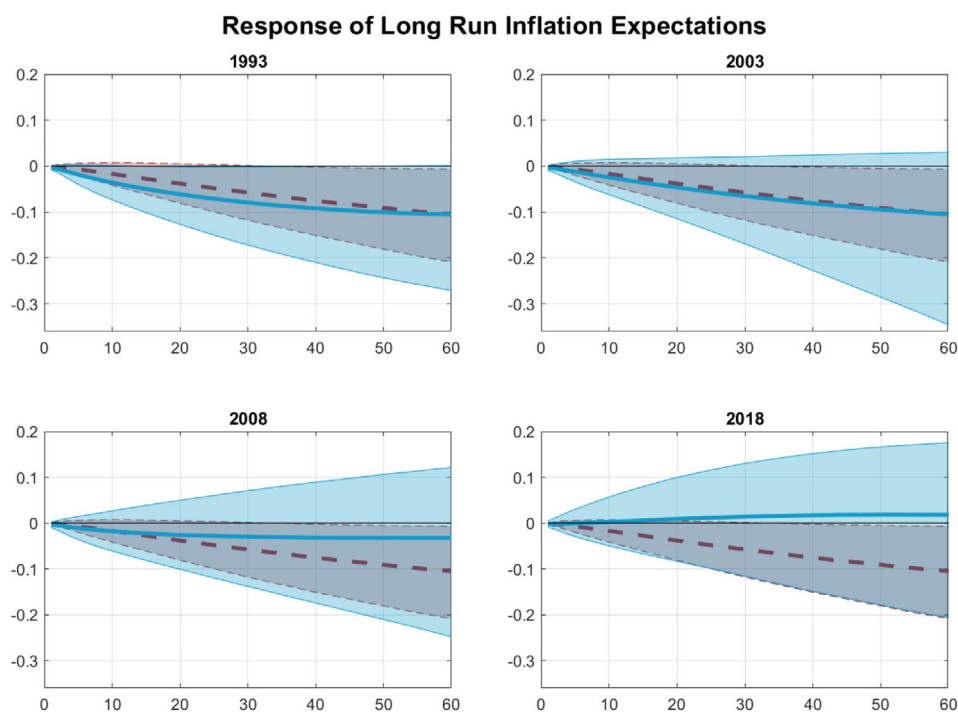


Figure 4. Impulse response of long-run inflation expectations following a monetary policy uncertainty shock, yearly averages. Solid line denotes the median response and shaded area is the 68% probability intervals for the time-varying parameter model. The dashed line is the response from a constant parameter case

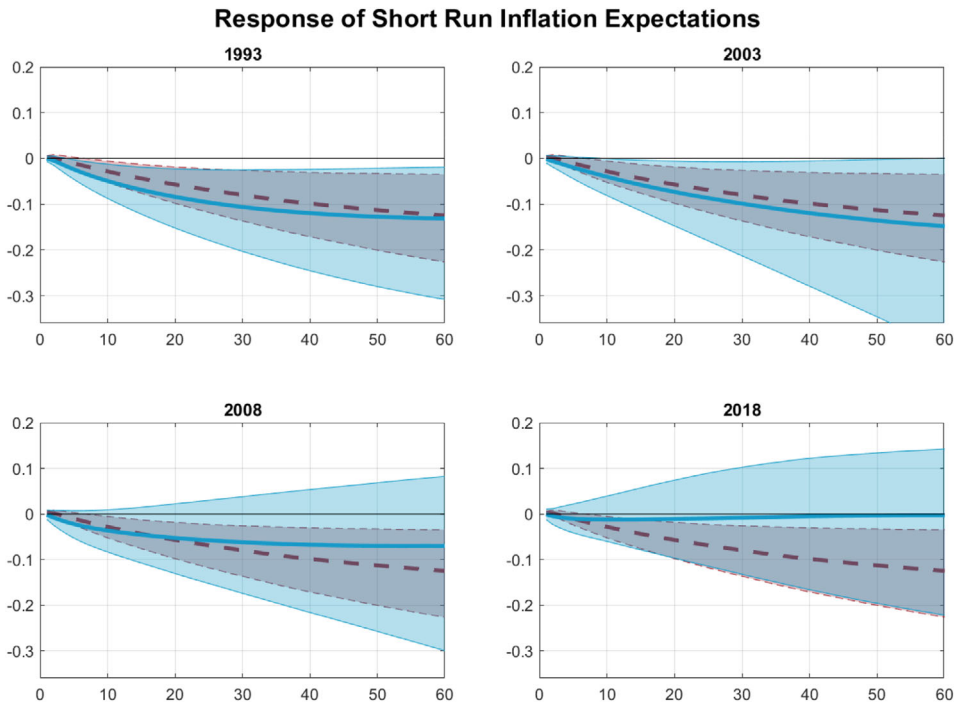


Figure 5. Impulse response of short-run inflation expectations following a monetary policy uncertainty shock, yearly averages. Solid line denotes the median response and shaded area is the 68% probability intervals for the time-varying parameter model. The dashed line is the response from a constant parameter model

shows the gradual transition towards the flat response throughout the last decade of low interest rates. Combined with the low estimated volatilities, this evidence points towards a strong anchoring of inflation expectations.

Figure 8 depicts the responses of unemployment and the monetary policy rate. Unemployment has always increased following an MPU shock, albeit in different magnitude. By far, the strongest response is estimated to be during the financial crisis, a result probably exacerbated through omitted variable bias as additional information is needed in the model to capture the sharp increase in unemployment during the crisis. Nevertheless, even in good times, a standard deviation shock in MPU increases unemployment by about 0.2% points.

Following an MPU shock, the response of the monetary policy rate mimics the dynamics of inflation – it has declined throughout the first half of the sample. However, after the financial crisis, interest rates do not seem to react anymore. Thus, it appears that the importance of MPU shocks has declined in recent years. Mumtaz and Theodoridis (2018) also show highlighted that uncertainty shocks, namely macro uncertainty, have become less important over time, specifically towards real and financial variables. However, they do not find this for prices. Our results suggest that at least MPU has become less important for inflation, yet only in the recent periods not covered by their sample. A further distinction is that our real variable, unemployment, reacts stronger to an MPU



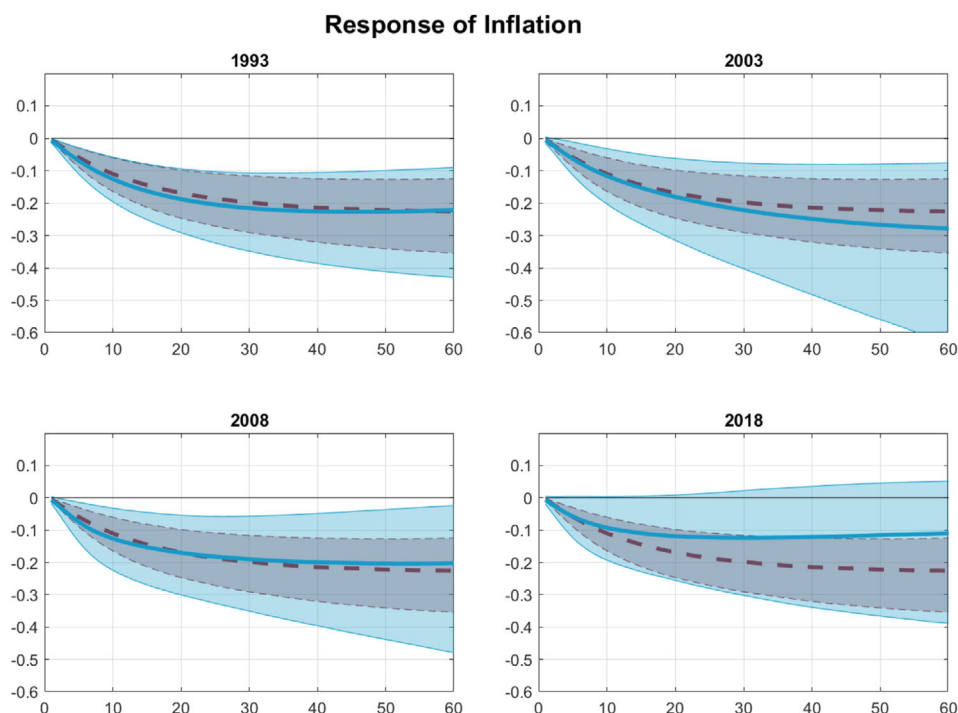


Figure 6. Impulse response of inflation following a monetary policy uncertainty shock, yearly averages. Solid line denotes the median response and shaded area is the 68% probability intervals for the time-varying parameter model. The dashed line is the response from a constant parameter model

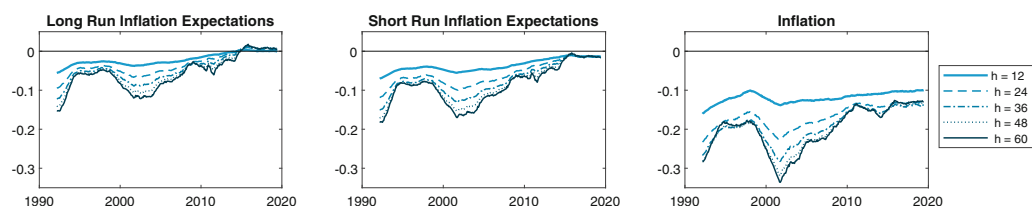


Figure 7. Cross section of the median impulse responses at specific horizons after the shock – from  $h = 12$  months to  $h = 60$  months

shock during and after the GFC, which is in line with other contributions in the literature, such as Angelini *et al.* (2019) and Alessandri and Mumtaz (2019).

These findings may also be related to a large strand of the literature on state dependent effects of uncertainty (Caggiano *et al.*, 2014; Caggiano, Castelnuevo and Pellegrino, 2017; Castelnuevo and Pellegrino, 2018; Liu *et al.*, 2019).<sup>13</sup> These contributions show that uncertainty shocks have had different effects throughout time, nonetheless by highlighting that the impact is more pronounced in recessionary periods. However, we find diminishing effects of MPU shocks over time (as, for example, also Mumtaz and Theodoridis (2018) do, albeit with respect to macro uncertainty). In part, this is explained by our model

<sup>13</sup>See Castelnuevo (2019) for an overview of the literature.



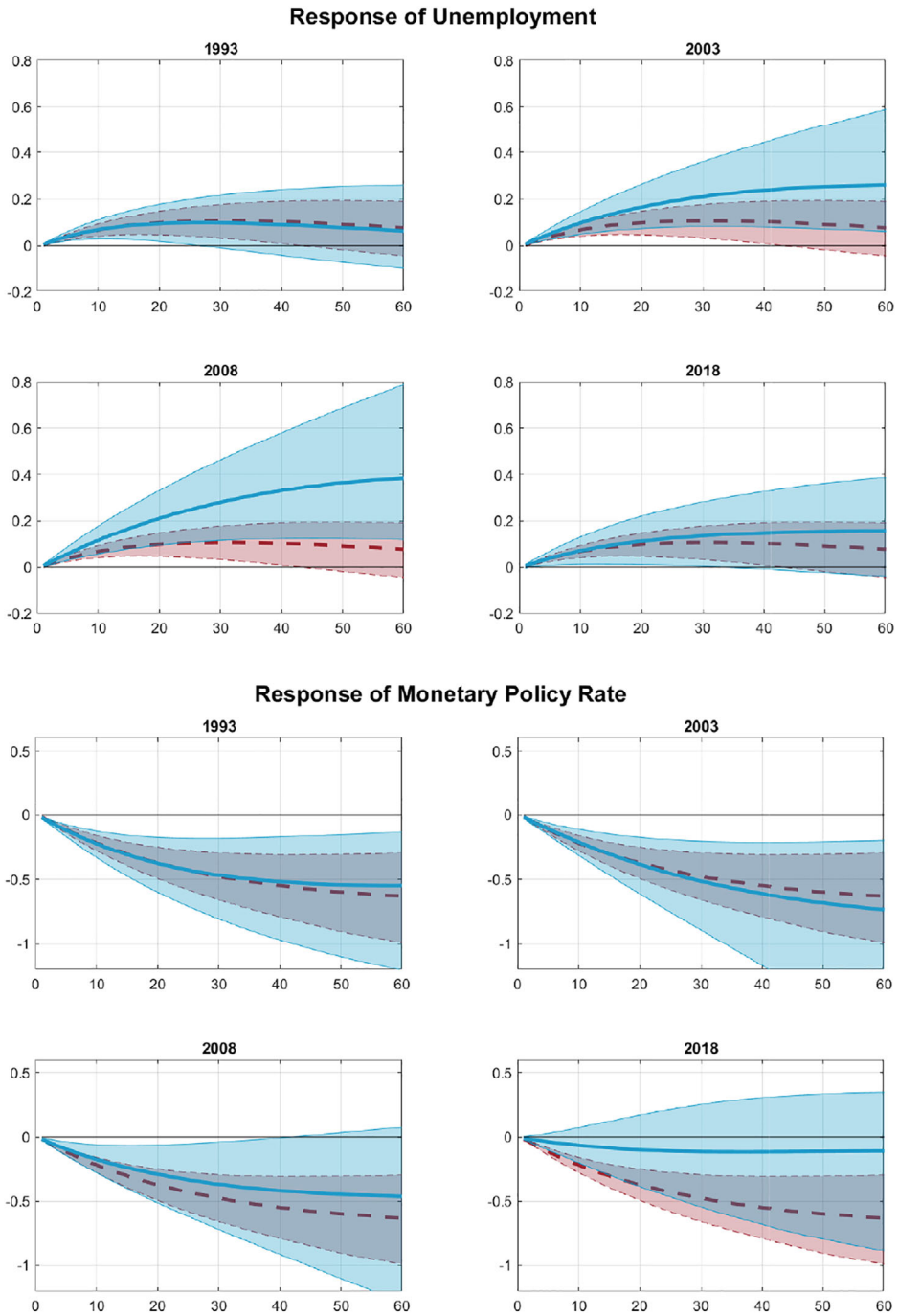


Figure 8. Impulse responses unemployment and monetary policy rate following a monetary policy uncertainty shock, yearly averages. Solid line denotes the median response and shaded area is the 68% probability interval for the time-varying parameter model. The dashed line is the response from a constant parameter model

choice – we allow for a gradual parameter evolution to capture long-run changes of the macroeconomic dynamics. The state dependent literature, on the other hand, utilizes models that allow for large and sudden parameter breaks, such as change-point, threshold, and smooth-transition approaches.

Furthermore, the VAR structure imposes that all variables are interconnected – as the monetary policy rate reacts less to MPU shocks over time, the other variables might do so as well. For example, Liu *et al.* (2019) show that first-moment demand shocks suppress prices and interest rates, while unemployment rises.<sup>14</sup> However, we show that second-moment shocks matter also on their own – the median response of the monetary policy rate is almost flat towards the end of our sample 2018, while inflation and unemployment continue to react to MPU shocks.

Finally, the model is robust with regard to different specifications. We have explored robustness with respect to the number of lags, the variables included, and their ordering. Notably, given the importance of the macro-financial nexus, we test for a possible omitted variable bias by including a financial variable, namely the S&P500 returns. We find that controlling for financial uncertainty does not alter the estimated proxy for MPU shocks, neither it affects the impulse response analysis. Moreover, the model implied financial uncertainty from the S&P500 appears to match rather well the financial uncertainty index by Jurado *et al.* (2015). These findings are reported in the Appendix, Section C. Furthermore, changing the order of the variables, a prominent issue with SVAR models with Cholesky decomposition and even more so with TVP-VARs, does not lead to different conclusions (Figures C4 and C5 in Section C in the Appendix).

## VI. Concluding remarks

In this article, we investigate the evolution of monetary policy uncertainty on the economy, with a special focus on the consequences of unexpected increases of MPU on inflation expectations. Using monthly data for the United States, we estimate an SVAR with stochastic volatility-in-mean. Starting with a constant parameter specification, we find further evidence that MPU shocks act as negative demand shocks with rising unemployment and decreasing price level. More importantly, we find that inflation expectations react negatively to an increase in the MPU with a different magnitude for long and short inflation expectations.

Considering the evidence that inflation expectations differ across age groups and personal experience, we then estimate a model where we allow the parameters among the model variables to change over time. We treat the question of how much parameter evolution is allowed in the model as open and estimate it from the data.

This extension allows us to observe that long-run and short-run inflation expectations have reacted differently to MPU shocks in the 90s as opposed to today. Long-run inflation expectations have remained mostly robust and unperturbed by MPU shocks apart from the beginning of the 90s. On the other hand, short-run inflation expectations have had a pronounced negative response up to the Great Recession. After the 2008 crisis, short-run

<sup>14</sup>The original paper reports the results to a positive demand shock from a change-point VAR model identified via sign restrictions conditioning on the regime. Thus, the model should preserve its signs following a negative demand shock.

inflation expectations have become less and less affected by MPU shocks. This finding is surprising given that most episodes associated with high MPU have occurred after 2008. This distinction between long- and short-run inflation expectations suggests a level of rigidity surrounding long-run inflation expectations associated with a credible central bank. Contrary to short-run inflation expectations, inflation reacts negatively throughout the whole sample and more strongly than the inflation expectations in the short run Jurado *et al.* (2015).

Overall we find that MPU shocks have become less important over time. This is true not only for inflation expectations and inflation but also for unemployment and the interest rate. These findings suggest that MPU might be less obstructing for the conduct of monetary policy than perceived. Neither interest rates react nowadays to MPU shocks as they did in the past, nor inflation expectations appear to respond as much as historically observed.

## APPENDIX A: TVP model

The posterior density of the  $k_Q$  parameter is plotted in Figure A1.

The strong evidence for time variation in the data is also supported in the estimated stochastic volatilities. As the relationship between the variables changes, the degrees of freedom for the model to fit the data increase, hence the stochastic volatility declines. We find that while the most important events of the estimated MPU remain the same across both specifications, the MPU estimated under the TVP model is markedly lower after the dot-com bubble (Figure A2).

## APPENDIX B: Monte Carlo simulation

The data generating process (DGP) for the Monte Carlo simulations is given by

$$Z_t = \hat{c} + \sum_{j=1}^P \hat{\beta}_j Z_{t-j} + \sum_{m=0}^M \hat{\gamma}_m \tilde{h}_{t-m} + u_t, \quad u_t \sim N(0, \hat{\Omega}_t), \quad (\text{B1})$$

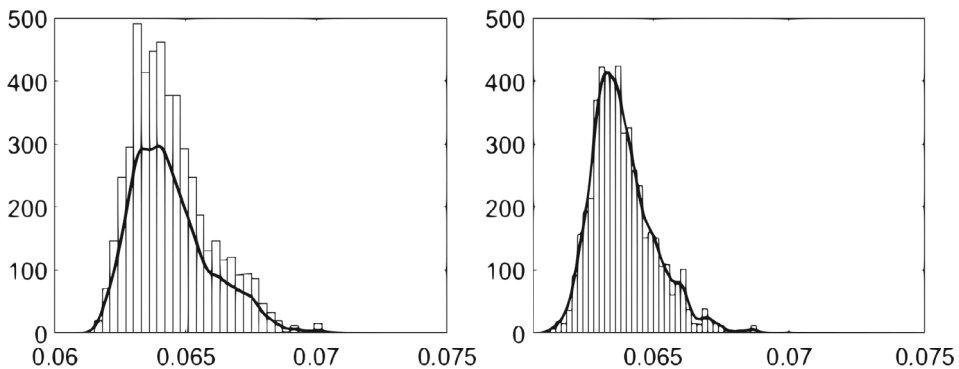


Figure A1. Posterior densities of the time-variation parameter  $k_Q$ . Left: Shadow short rate model. Right: Federal funds rate model

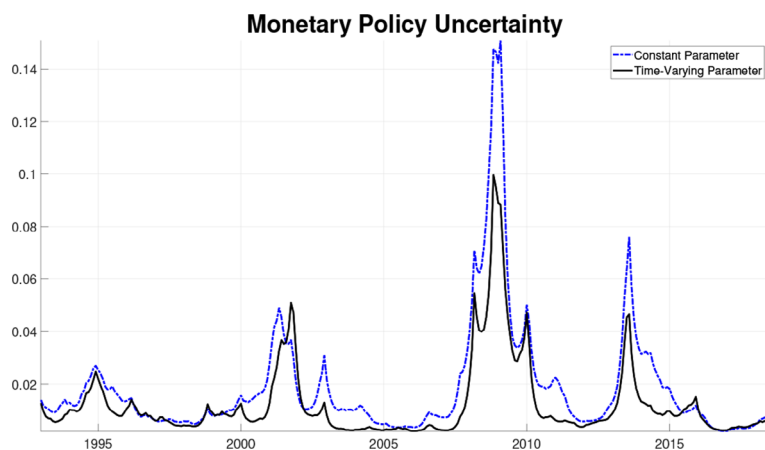


Figure A2. Median estimates of Monetary Policy Uncertainty from a model with time-varying parameters versus the constant coefficient specification

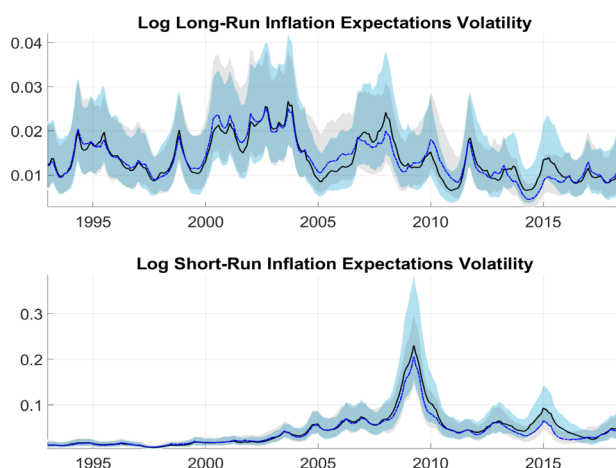


Figure A3. Log volatilities of short- and long-run inflation expectations based on a model with the SSR (solid line) and a FED Funds model (blue dashed line) with 68% probability intervals

with  $\hat{\Omega}_t = \hat{A}^{-1} H_t \hat{A}^{-1'}$  where  $H$  is specified as in the original set-up as being a diagonal matrix with  $\tilde{h}$  on the diagonal. The parameters of the DGP are set at the posterior mode from the estimation of the model based on real data, which ensures a stable VAR process. We then proceed to draw a series of shocks for  $u_t$  for  $t = 1, \dots, 500$ , which is in line with the sample size we have in practice. To draw from  $N(0, \hat{\Omega}_t)$  we need to specify a series for  $\tilde{h}_t$ . The shapes of the true volatility series are inspired by the estimates with the real data – we clone the first 250 observations from our model twice, thus creating a data set with two large crises. This results in a couple of large peaks in long-run inflation volatility in the first set-up (MC1), while we force short-run inflation volatility to be extremely low with a mean at 0.005. Correspondingly in the second set-up (MC2), we adopt a low long-run volatility series, similar to the one in the real data.

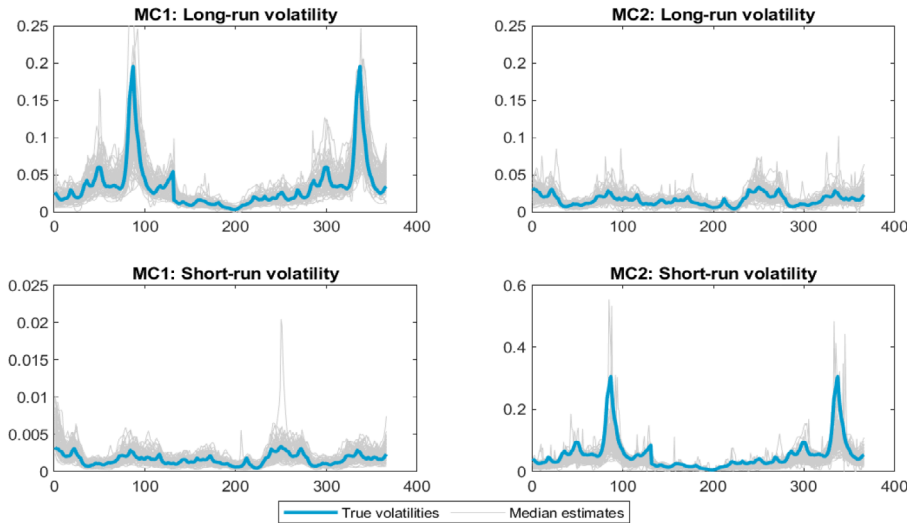


Figure B1. True versus estimated volatility from 200 Monte Carlo simulations. Left: Monte Carlo set-up 1 (MC1) with high long-run inflation volatility and low short-run inflation volatility. Right: Monte Carlo set-up 2 (MC2) with high short-run inflation volatility

We then proceed to draw 200 data sets, 100 for each set-up and estimate the model 200 times. After each estimation, we have an uncertainty measure for long- and short-run inflation expectations and its probability intervals. In Figure B1, we plot the median volatility estimates for each data set (100 per set-up) along with the true DGP from which said data set was created. We find that the model correctly captures the shape of each special case. Note that each grey line on the graph is the median outcome of one data set; for ease of readability, we omit the probability intervals surrounding each run.

## APPENDIX C: Robustness section

### Robustness to the lag specification

Figure C1 plots the impulse responses of the constant parameter models the federal funds rate with 12 lags. The only quantitative difference is the case of long-run inflation expectations with the SSR, where the response is significant, while the FED Funds model shows identical behaviour to the two lag SSR specification.

### Extending the model to control for financial uncertainty

Figure C2 indicate that our baseline stochastic volatility estimates, from which our monetary policy uncertainty measure is derived, are unaffected by including the S&P 500 returns as in Mumtaz and Zanetti (2013) to account for financial uncertainty. Additionally, one can observe that despite the fact that the monetary policy uncertainty from the financial model follows very closely the estimates from the baseline one, the estimated volatility of the S&P 500 returns differs significantly from the monetary policy uncertainty measure. Moreover, Figure C3 shows the associated financial uncertainty from the model

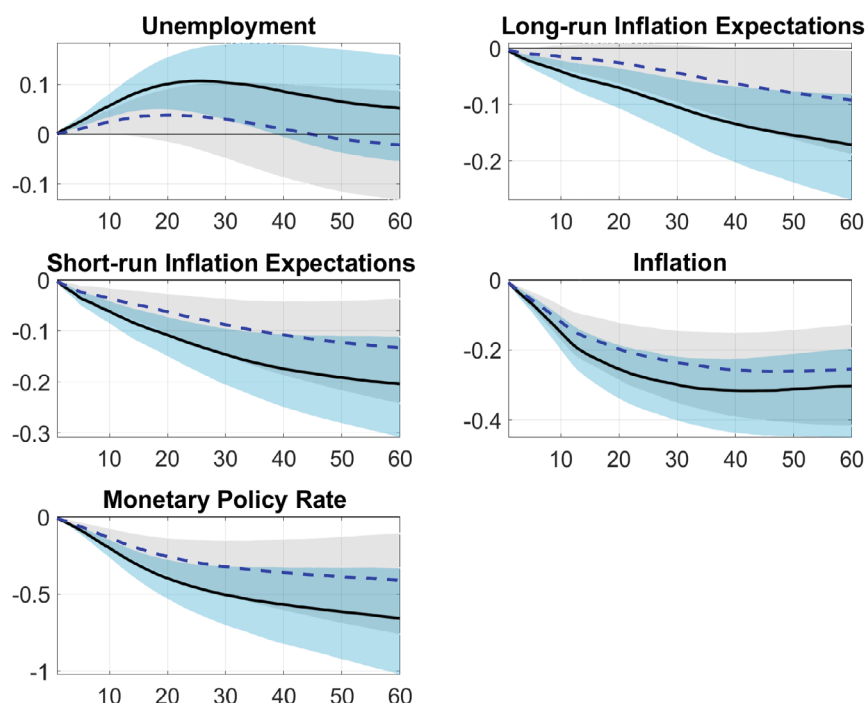


Figure C1. Median responses to a monetary policy uncertainty shock. Model with shadow short rate (solid line) and model with the federal funds rate (dashed line). The shaded areas show the 68% probability interval

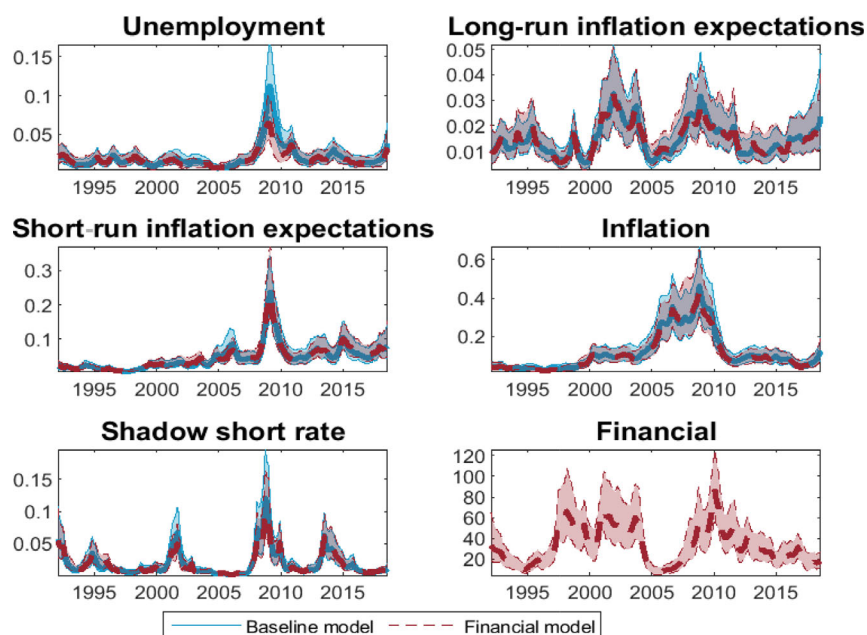


Figure C2. Solid blue line depicts the median estimate of the stochastic volatilities of the baseline model. Dashed red lines are the median estimates of the stochastic volatilities of the alternative financial specification. Shaded areas show the corresponding 68% probability intervals

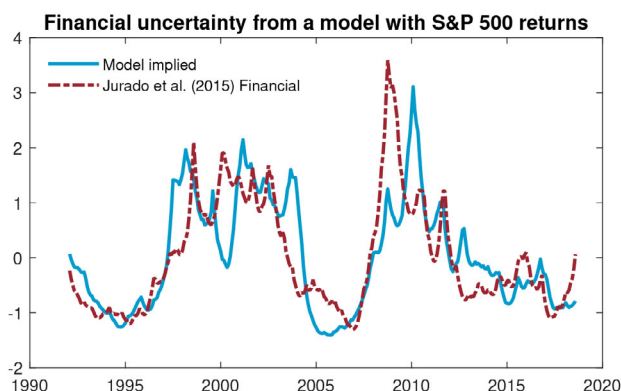


Figure C3. Comparison between financial uncertainty estimated from the model by extending it with S&P 500 returns and plotting the stochastic volatility to its shocks versus Jurado *et al.* (2015)

the alternative financial model of Figure C2 appear to coincide well with the financial uncertainty index of Jurado *et al.* (2015).

### Robustness to the variable order

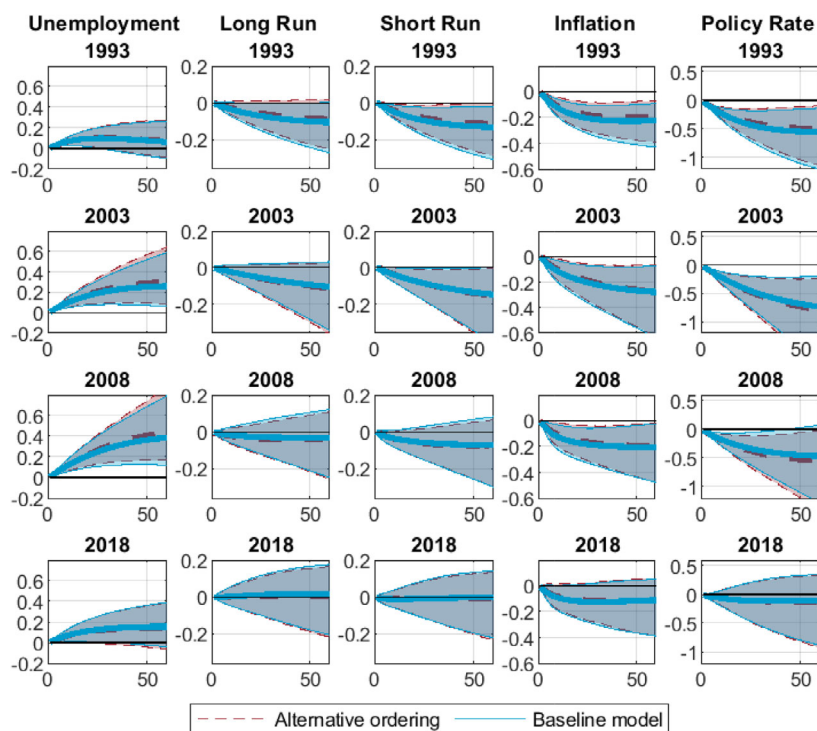


Figure C4. Solid blue line depicts the median responses to a monetary policy uncertainty shock of the baseline model at different time periods. Dashed red lines are the median responses to a monetary policy uncertainty shock of the alternative ordering specification. Shaded areas show the corresponding 68% probability intervals



### Impulse responses: Unemployment uncertainty shock

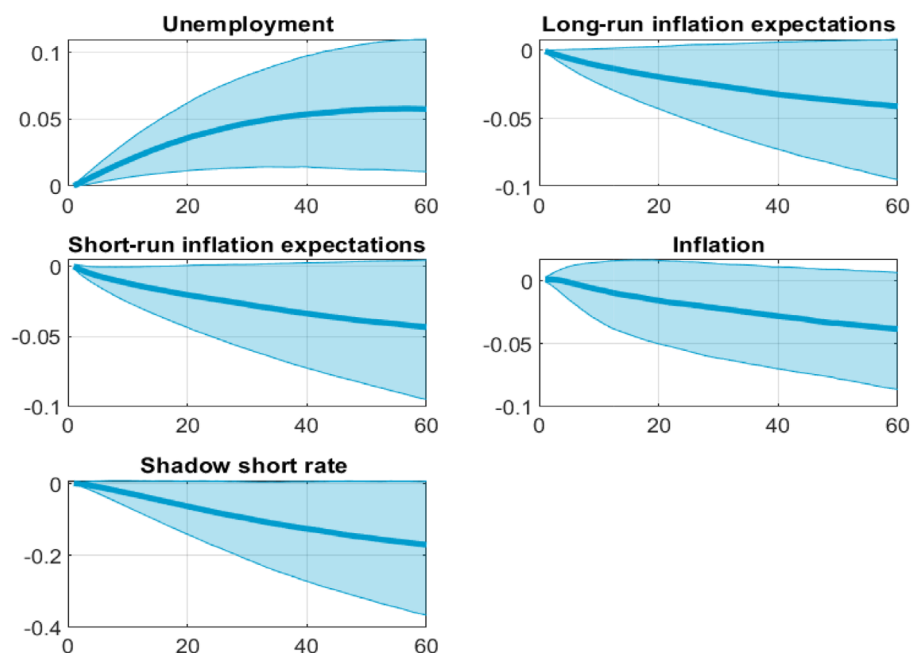


Figure C5. Solid blue line depicts the median responses to a unemployment uncertainty shock of the baseline model. Shaded areas show the corresponding 68% probability intervals

## APPENDIX D: Convergence

To ensure convergence of the Gibbs sampler, we estimate the recursive means of the retained draws for the time-varying parameters and stochastic volatilities of the baseline model. Figures D1 and D2 present the recursive means for every 20 draws of the vectorized

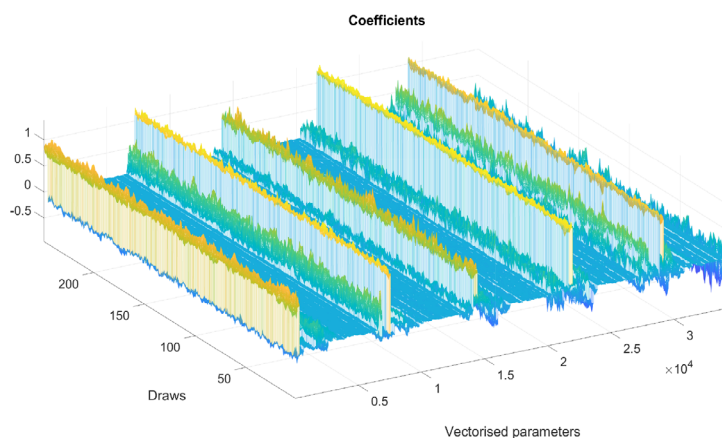


Figure D1. Recursive means of the VAR coefficients

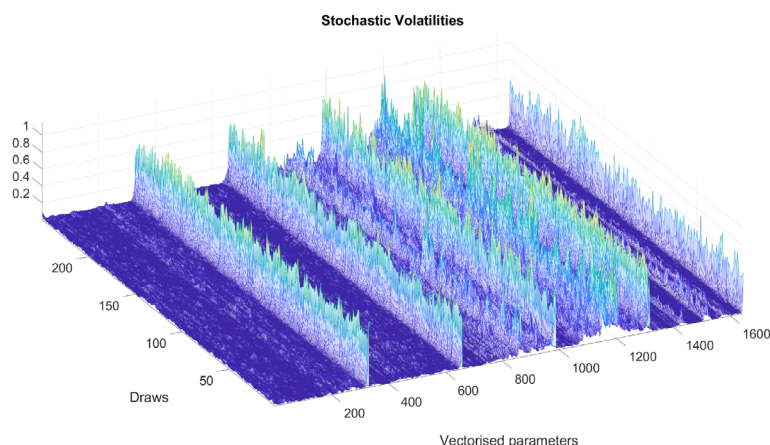


Figure D2. Recursive means of the volatilities

time-varying parameters and stochastic volatilities. Both graphs suggest convergence in the Gibbs sampler given that along the different draws, the recursive means remain stable and do not depict any sudden increase among the different draws.

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