Of Votes and Viruses: The UK Economy and Economic Policy Uncertainty

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Abstract

This paper examines the relation between GDP growth, Divisia money growth, CPI inflation, financial stress, and the United Kingdom's economic policy uncertainty in the context of its departure from the European Union. We employ two Bayesian VAR models which account for the extreme observations in macroeconomic and financial time series resulting from the COVID-19 pandemic outbreak. We document a contractionary effect of an economic policy uncertainty shock on GDP growth, which is not present in a model which does not account for the COVID-19-related outliers. Additionally, we find that GDP growth is enhanced by Divisia monetary stimulus but hampered by increases in financial stress. The results from a stochastic volatility in mean threshold model also uncover different dynamics of transmission of shocks between economic uncertainty and the indicators we study across high and low economic policy uncertainty regimes.

JEL: E52, C30, C51

Keywords: Brexit, COVID-19, Economic Policy Uncertainty, VAR models.

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1 Introduction

In his 2013 Nobel Memorial Prize in Economics Sciences lecture, Lars Peter Hansen notes: "Part of a meaningful quantitative analysis is to look at models and try to figure out their deficiencies and the ways in which they can be improved." Rare, extreme events, such as the COVID-19 pandemic, produce significant outliers in macroeconomic data, which in turn impede inference from many econometric models. Several studies propose different strategies of accounting for the impact of such events on key variables used in vector autoregressions (VARs), the workhorse of modern macro-econometric modelling. For instance, Lenza and Primiceri (2020) propose a method of re-scaling the standard deviations of shock volatilities during the months associated with the most substantial movements in macroeconomic indicators brought by the pandemic. Other methods put forward to reliably estimate and produce forecasts from VAR models incorporating the most recent data include accounting for threshold effects in the model (Chudik et al., 2020) or adopting a time-varying stochastic volatility model for the VAR residuals (Carriero et al., 2021).

This paper examines the economic impact of the United Kingdom's decision to leave the European Union (EU) in June 2016 and its eventual departure in December 2020 through the lens of economic policy uncertainty (EPU). The econometric issues outlined above are particularly pertinent in the context of this question, as undertaking such analysis requires one to reliably separate the economic influence of the COVID-19 pandemic from that of leaving the single market. To that end, we base our study on two Bayesian VAR models. The first model accounts for the outliers in the UK macroeconomic and financial data due to the pandemic. The second is a non-linear model which incorporates stochastic volatility and distinguishes between periods of high and low economic policy uncertainty.

EPU indices pick up key words relating to economic policy uncertainty from major newspapers in a given country (or worldwide). Following the seminal work by Baker et al. (2016), studies on the impact of EPU on the real economy and financial markets are growing (see, e.g., Caldara et al., 2016; Nilavongse et al., 2020; Caggiano et al., 2020).[1]

We plot the UK's economic policy uncertainty index in Figure 1. Following the decision to leave the EU on 23 June 2016, the UK's EPU index peaks in July 2016 at an all-time high of 558.22 points. These high levels of EPU persist until early 2018 before rising again and remaining high until the end of 2020 when the UK left the EU. The dynamics of the EPU index during the period we study conform with the view that the Brexit referendum has been by far the most significant event so far in the post-war British political history

[1] Steinberg (2019) assesses the macroeconomic impact of trade policy uncertainty in conjunction with Brexit.

and are an accurate representation of the volatile nature of the negotiations on the UK's future relationship with the bloc that took place between 2017 and 2020.

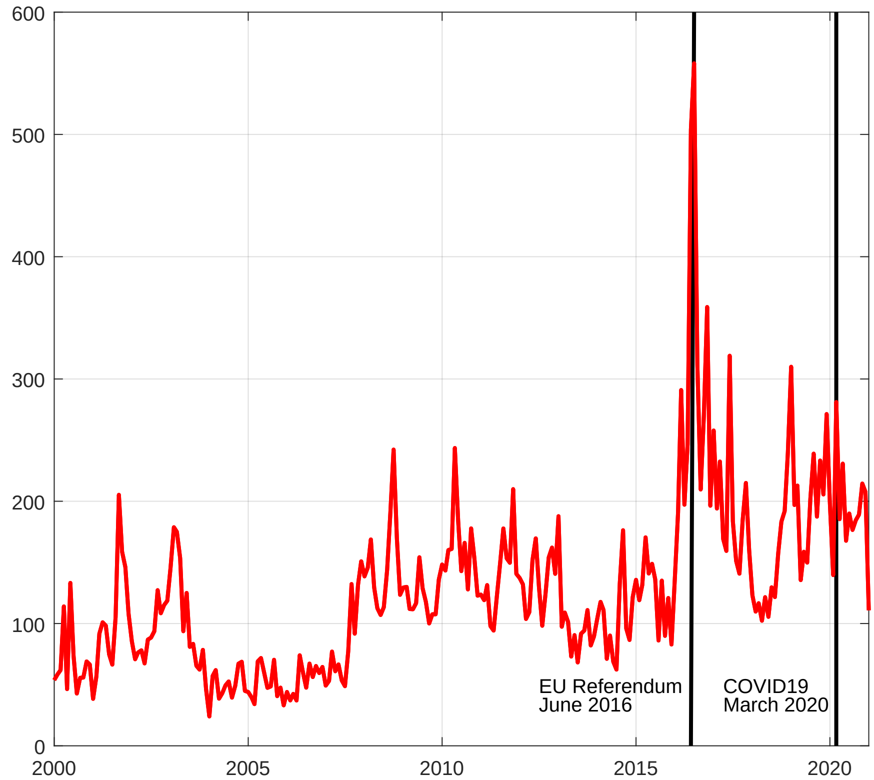

Figure 1: **UK Economic Policy Uncertainty Index (Baker et al., 2016)**
Notes: This figure plots the UK Economic Policy Uncertainty Index of Baker et al. (2016) from January 2000 to January 2021. The leftmost vertical line refers to the month of the EU referendum, June 2016. The rightmost vertical line refers to the first month of the accelerated spread of the COVID-19 virus in the UK, March 2020.

The results we document show a contractionary effect of economic policy uncertainty on UK GDP growth, which persists for approximately 12 months following a shock. We find that such effect can only be identified if the outliers in macroeconomic and financial data brought by the COVID-19 pandemic are appropriately accounted for in the model. We also establish that Divisia monetary stimulus encourages further GDP growth for up to 10 months, whereas an increase in financial stress leads to contractionary effects which may last for as many as 20 months. Finally, our estimates demonstrate that economic policy uncertainty shocks result in spillover effects influencing financial markets, which are more pronounced during the periods when economic policy uncertainty is already high.

Overall, our findings demonstrate that policy uncertainty is a significant driver of the United Kingdom's economic growth, over and above the expansionary impact of monetary policy and the contractionary effects of financial stress. While we demonstrate that GDP growth and inflation respond negatively to economic uncertainty shocks, especially in the high economic policy uncertainty regime in the aftermath of the Brexit referendum, due to the nature of the models and data availability it is not possible to disentangle the individual effects of the departure from the European Union from those of the COVID-19 pandemic. That notwithstanding, the results we document are of particular relevance in the context of policy design and evaluation, as we provide clear and robust evidence demonstrating the need for macroeconomic models to adequately accommodate the substantial outliers in the data in order to support meaningful analysis of the impact of key events on the real economy.

2 Data and Econometric Models

2.1 Data

We use monthly UK economic data from January 2000 to January 2021. The sample period is determined by data availability. Economic policy uncertainty (EPU) is the Baker et al. (2016) UK economic policy uncertainty index available from policyuncertainty.com. Monthly Gross Domestic Product (GDP) and Consumer Price inflation (CPI) metrics are from the Office for National Statistics (ONS). Our monetary policy variable is the Divisia money (DM) aggregate from the Bank of England's statistical database. Keating et al. (2014, 2019) show empirically and theoretically that the broadest Divisia monetary aggregate feasibly acts as a monetary policy variable, which allows one to capture monetary policy stance when interest rates approach their effective lower bound. Further empirical benefits of Divisia for macroeconometric modelling are discussed in detail in Ellington (2018) and Ellington and Michalski (2021).

Our financial stress indicator is the European Central Bank's (ECB) financial stress (FS) index available from the ECB's Statistical Data Warehouse. The FS index pools information on the volatility of: i) the real effective exchange rate; ii) the equity market; and iii) the bond market (using the volatility of the 10-year government bond yield). Further details are available in Duprey et al. (2017). EPU and FS enter our models in levels, whereas GDP, CPI and DM enter as annual growth rates that we compute as conventional percent changes. Figure 8 in the Appendix provides data plots of all variables we examine.

2.2 Econometric Models

2.2.1 Accounting for Outliers during the COVID-19 Pandemic in a VAR Model

In order to account for outliers in the macro-financial variables our initial analysis follows the procedure in Lenza and Primiceri (2020). This involves scaling the VAR's covariance matrix at the point when the spread of the COVID-19 pandemic accelerates in March 2020. The VAR(p) model is written as follows:

$$y_t = B_0 + \sum_{i=1}^{p} \mathbf{B}_i y_{t-i} + s_t \varepsilon_t, \;\; \varepsilon_t \backsim \mathrm{N}\left(0, \mathbf{\Sigma}\right) \tag{1}$$

where y_t is an $n \times 1$ vector of variables, B_0 is a vector of constants, $\mathbf{B}_i$ are conformable matrices of autoregressive coefficients, and ε_t is an $n \times 1$ vector of residuals with $\mathbf{\Sigma}$ being the covariance matrix. s_t is a variable that is equal to 1 prior to March 2020. We label March 2020 as period t^*, during which $s_{t^*} = \bar{s}_0$. At periods $t^* + 1$, $t^* + 2$, $s_{t^*+1} = \bar{s}_1$ and $s_{t^*+2} = \bar{s}_2$, respectively. At periods $t^* + j$ we have $s_{t^*+j} = 1 + (\bar{s}_2 - 1)\,\rho^{j-2}$. Let $\theta \equiv [\bar{s}_0, \bar{s}_1, \bar{s}_2, \rho]$ be a vector of unknown coefficients that we need to estimate. This allows the scaling factor to take three possibly different values in March, April and May of 2020 and to decay at rate $1 - \rho$ thereafter.

To estimate a VAR on time-series data including the pandemic, we rewrite Equation (1) as

$$y_t = X_t \beta + s_t \varepsilon_t \tag{2}$$

where $X_t \otimes x_t'$, $x_t \equiv \left[1, y_{t-1}', \ldots, y_{t-p}'\right]$ and $\beta \equiv \mathrm{vec}\left([B_0, \mathbf{B}_1, \ldots, \mathbf{B}_p]\right)$. Dividing both sides by s_t we have

$$\tilde{y}_t = \tilde{X}_t \beta + \varepsilon_t \tag{3}$$

with $\tilde{y}_t = y_t / s_t$, $\tilde{X}_t = X_t / s_t$ which are transformations of the original data. We estimate the parameters β, $\mathbf{\Sigma}$ from Equation (3) using Bayesian methods. Specifically, we adopt a standard Minnesota prior for the VAR coefficients and an inverse-Wishart prior for the VAR covariance matrix. We estimate the model following Lenza and Primiceri (2020) and Giannone et al. (2015), with the former providing the details on prior specifications and posterior simulation.

2.2.2 A Stochastic Volatility in Mean Threshold VAR Model

Our next point of analysis incorporates stochastic volatility into a VAR model that influences the first-moment dynamics of the system. Similar to Alessandri and Mumtaz (2019), we further allow dynamics to be conditional on the level of economic policy uncertainty, which characterises periods of high and low economic policy uncertainty. Our stochastic volatility in mean threshold VAR (SVOL-IM-TVAR) model is specified as follows:

$$\begin{aligned} y_t = & \left(\mathrm{B}_{1,0} + \sum_{i=1}^{p} \mathbf{B}_{1,i} y_{t-i} + \sum_{j=0}^{J} \gamma_{1,j} \ln \lambda_{t-j} + \boldsymbol{\Sigma}_{1,t}^{1/2} \varepsilon_t \right) \mathrm{S}_t \\ & + \left(\mathrm{B}_{2,0} + \sum_{i=1}^{p} \mathbf{B}_{2,i} y_{t-i} + \sum_{j=0}^{J} \gamma_{2,j} \ln \lambda_{t-j} + \boldsymbol{\Sigma}_{2,t}^{1/2} \varepsilon_t \right) (1 - \mathrm{S}_t) \end{aligned} \tag{4}$$

where y_t is an $n \times 1$ vector of variables, $\mathrm{B}_{k,0}$, $k = \{1, 2\}$ are the regime-specific vectors of intercepts and $\mathbf{B}_{k,i}$ are the matrices of autoregressive coefficients in regime $k = \{1, 2\}$ at the $i = 1, 2, \ldots, p$ lags. The $\gamma_{k,j}$ coefficients show how each endogenous variable responds to uncertainty, λ_t, at lags $j = 0, 1, 2, 3$ in regime $k = \{1, 2\}$. λ_t is an unobservable state variable that we obtain by exploiting the volatility shocks throughout the estimation sample; we further define uncertainty in this context below. The introduction of S_t defines two regimes that characterise possibly different dynamics. In our case, the level of EPU relative to a threshold value, Z^*, governs regimes such that:

$$\mathrm{S}_t = 1 \Leftrightarrow \mathrm{EPU}_{t-d} \leq Z^* \tag{5}$$

where both the delay parameter, d, and the threshold value, Z^*, are unknown parameters. The regime-specific covariance matrices are of the form:

$$\boldsymbol{\Sigma}_{k,t} = \mathbf{A}_k^{-1} \mathbf{H}_t \mathbf{A}_k^{-1'}, \quad k = \{1, 2\} \tag{6}$$

where $\mathbf{A}_k$, $k = \{1, 2\}$ are lower-triangular matrices containing contemporaneous covariances in regime k. The volatility process is of the form:

$$\mathbf{H}_t = \lambda_t \mathbf{G} \tag{7}$$

$$\mathbf{G} = \operatorname{diag}(g_1, g_2, g_3, g_4, g_5) \tag{8}$$

$$\ln \lambda_t = \mathrm{a} + \mathbf{F} \ln \lambda_{t-1} + \eta_t, \quad \eta_t \backsim^{iid} (0, Q) \tag{9}$$

λ_t is a scalar volatility process that drives time variation for the covariance matrix of structural shocks. The diagonal matrix $\mathbf{G}$ contains loadings on the volatility process for each of the $n = 5$ endogenous variables. This process is a popular modelling assumption that many studies use variants of (see, e.g., Carriero et al., 2016; Alessandri and Mumtaz, 2019; Chan, 2020; Ellington, 2021). Overall, this model distinguishes between periods of high and low EPU and allows for regime-specific parameters to govern dynamics in each regime. The inclusion of economic uncertainty in the mean equations also allows macroeconomic and financial variables to also adjust to overall economic uncertainty. We place no restriction on how ε_t, η_t evolve in each regime.

Details of the prior specification and posterior simulation algorithm are in the Online Appendix of Alessandri and Mumtaz (2019). In essence, given a draw of λ_t, the model collapses to a standard threshold VAR (TVAR) with a known form of heteroskedasticity. After a generalised least squares transformation, the conditional posterior distribution of VAR parameters, the threshold value, and delay parameter are identical to a standard TVAR model (Alessandri and Mumtaz, 2017). The conditional posterior of the delay is a multinomial distribution (Chen and Lee, 1995). The threshold value is drawn from a non-standard posterior via a Metropolis step. Then data is split to regime-specific observations and draws are taken from the Normal distribution. Once we have the residuals of the VAR and λ_t, the conditional posterior of $\mathbf{A}_k$ is standard (e.g. Cogley and Sargent, 2005). Finally, λ_t is drawn using the independence Metropolis step for stochastic volatility models as in Jacquier et al. (2002). We use the first 24 months of data to obtain the initial conditions of the model.

For both of the above models we set the number of lags to p=13, and allow 50,000 runs of each of the Markov Chain Monte Carlo (MCMC) algorithms. We discard the initial 25,000 draws and conduct inference on the remaining 25,000 from the posterior distribution. Our economic data enter the vector in the following manner: $y_t \equiv (\text{EPU}_t, \text{GDP}_t, \text{CPI}_t, \text{DM}_t, \text{FS}_t)$.

3 Results

3.1 A Linear VAR and the Lenza and Primiceri (2020) Approach

To demonstrate the benefit of the residual volatility adjustment of Lenza and Primiceri (2020), we first present the impulse response functions with respect to a unit standard deviation shock to EPU in Figure 2. These results stem from a standard linear Bayesian VAR model using economic data for our 5 variables from January 2000 to January 2021. We plot the posterior median, along with the 68% error bounds as dark shaded areas, and 95% error bounds as light shaded areas. We report impulse responses over a 60-month horizon and identify shocks using a Cholesky decomposition.

The error bands widen for all variables as the impulse horizon increases. The high degree

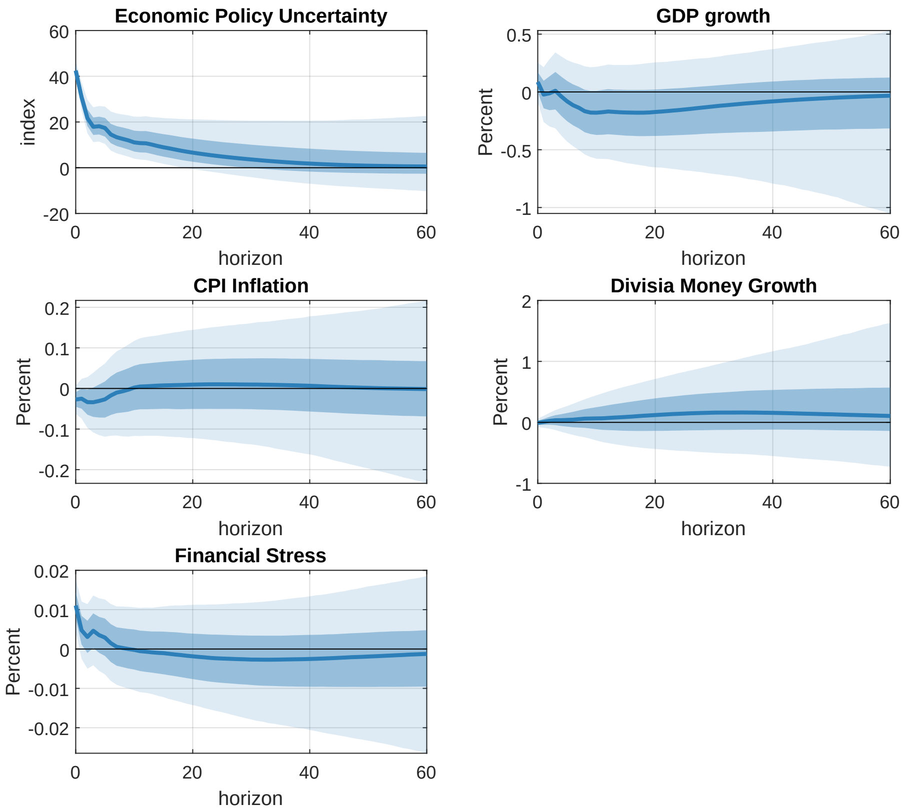

Figure 2: **Impulse Response Functions of UK Economic Variables with respect to an Economic Policy Uncertainty Shock from a linear Bayesian VAR**
Notes: This figure plots the impulse response functions of: economic policy uncertainty (EPU); GDP growth (GDP); CPI inflation (CPI); Divisia money growth (DM); and financial stress (FS), with respect to a one-standard deviation shock to economic policy uncertainty. We plot the responses over a 60-month horizon. Dark (light) shaded areas denote 68% (95%) error bounds.

of posterior uncertainty suggests a distortion in parameters and covariance matrix estimates and further highlights the issues with inference that Lenza and Primiceri (2020) note.[2] We also check all other impulse response functions from each model and observe the same, widening error bands as the impulse horizon rises and in some cases nonsensical impulse response functions. These results are available upon request.

We compare those results with analogous impulse response functions obtained from a linear Bayesian VAR model which accounts for the break in volatility beginning in March 2020, the start of COVID-19's rapid spread in the UK, which we report in Figure 3.

Scaling the VAR's covariance matrix during the period associated with the accelerating

[2]Plots of the posterior of the overall standard deviation of the Minnesota priors we use for each of the linear Bayesian VAR models are available upon request. These results show clear evidence of less shrinkage for the estimates of the coefficient matrices from the standard Bayesian VAR model which is the cost to pay for fitting the large variability of macroeconomic observations during the pandemic.

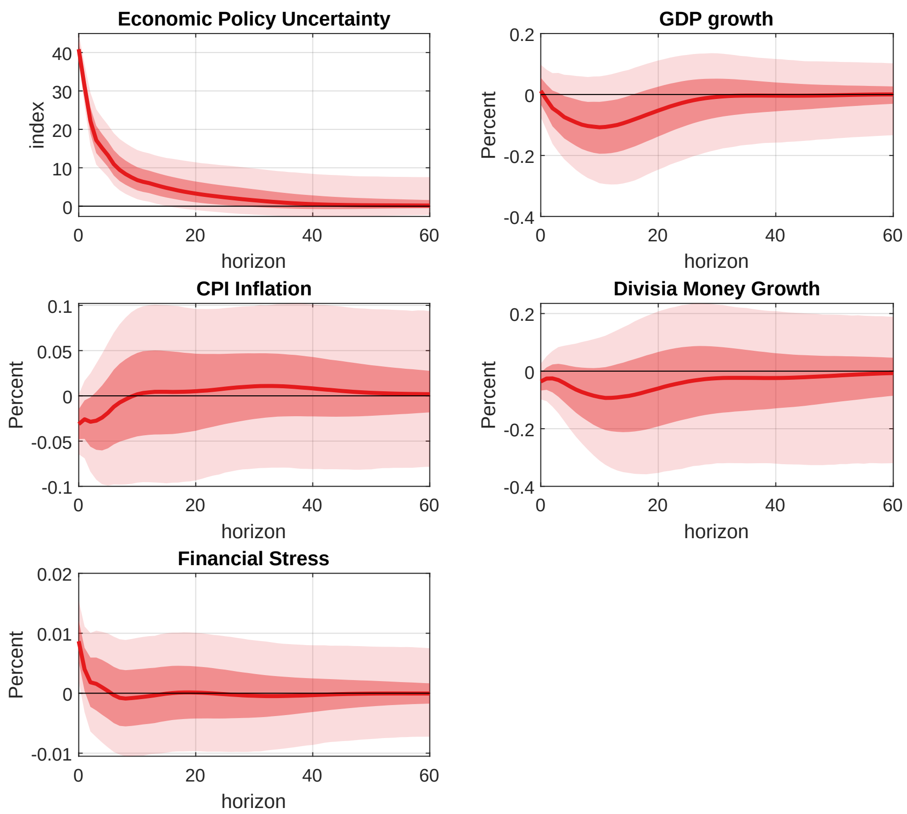

Figure 3: **Impulse Response Functions of UK Economic Variables with respect to an Economic Policy Uncertainty Shock from a Bayesian VAR with the Lenza and Primiceri (2020) Adjustment**
Notes: This figure plots the impulse response functions of: economic policy uncertainty (EPU); GDP growth (GDP); CPI inflation (CPI); Divisia money growth (DM); and financial stress (FS), with respect to a one-standard deviation shock to economic policy uncertainty. We plot the responses over a 60-month horizon. Dark (light) shaded areas denote 68% (95%) error bounds.

infection rates delivers a sensible degree of posterior uncertainty within the impulse response functions. The shocks to EPU result in a statistically significant contraction in GDP growth which lasts around 12 months. They also cause inflation and Divisia money growth to fall, while increasing financial stress. In general, the transmissions we observe here make sense economically. However, the long-term responses of the macroeconomic and financial variables to EPU shocks lack economic and statistical significance.

We also plot the impulse response functions for all variables with respect to Divisia money shocks and financial stress shocks in the Appendix (see Figures 9 and 10). The shocks to Divisia money are consistent in sign with an expansionary monetary policy shock, which stimulates UK GDP growth for up to 10 months. The shocks to financial stress also deliver economically plausible responses, for example, contractions to GDP growth and to Divisia money for as many as 20 months and 40 months, respectively. Additionally, as shown in Figure 8, Divisia money registered record growth rates in excess of 19% in early 2021, which, given its significance for CPI inflation (see Figure 9), could lead to inflation returning to, or even exceeding, the policymaker's 2% target during 2021.

3.2 The SVOL-IM-TVAR Model

The SVOL-IM-TVAR model, which we outline in Section 2.2.2, allows us to distinguish between periods of low and high economic policy uncertainty, and account for any possible regime-dependant effects of a shock. Estimates from this model span February 2003–January 2021 because we use 24 months to obtain the initial conditions and include 13 lags into the model. Figure 4 plots the UK EPU index and posterior modal threshold estimate, $Z^* = 141.04$, along with the periods when the UK economy is in a high EPU regime, $(1 - S_t)$, that we evaluate at the posterior mode against time. The delay parameter, d, at the posterior mode is equal to a 1-month lag, $d = 1$. We can see frequent regime switches throughout the 2008 recession and the slow recovery from the crisis. Furthermore, the model suggests a high EPU regime when the Bank of England abandons Forward Guidance tied to the unemployment rate in 2014. Importantly, the UK is in a high EPU regime from 2016 to early 2018, and then again from September 2018 until the end of the sample period, with the exception of two short periods in 2019 and early 2020. Those results serve as useful evidence of the magnitude of the shift in the UK's political landscape in the aftermath of the Brexit referendum.

We now turn to impulse response analysis and forecast error variance decompositions. We obtain impulse response functions using the Monte Carlo integration procedure of Koop et al. (1996). The regime-specific impulse response functions are the difference between two conditional expectations, one under a shock scenario and the other without. For each regime, we draw 500 random states of the economy, then simulate the model under each scenario, take the difference, and average over the histories. As before, we identify structural shocks using a Cholesky decomposition of the VAR's regime-specific covariance matrix.

Two points warrant further discussion. First, we treat regime-switching as endogenous, which means the economy can transition freely from the low EPU regime to the high EPU regime and vice-versa over the simulation horizon. Second, within a given regime the responses are conditional on the history of the system prior to the shock. This means the economy may respond differently when EPU is at its minimum and when it is just below the threshold even though each history is within the low EPU regime. We average over histories that belong to regime S_t=1 and S_t=0, respectively.

Figure 5 reports the impulse response functions for UK economic variables with respect to a 5-standard deviation shock to EPU. The top row shows responses in the low EPU regime

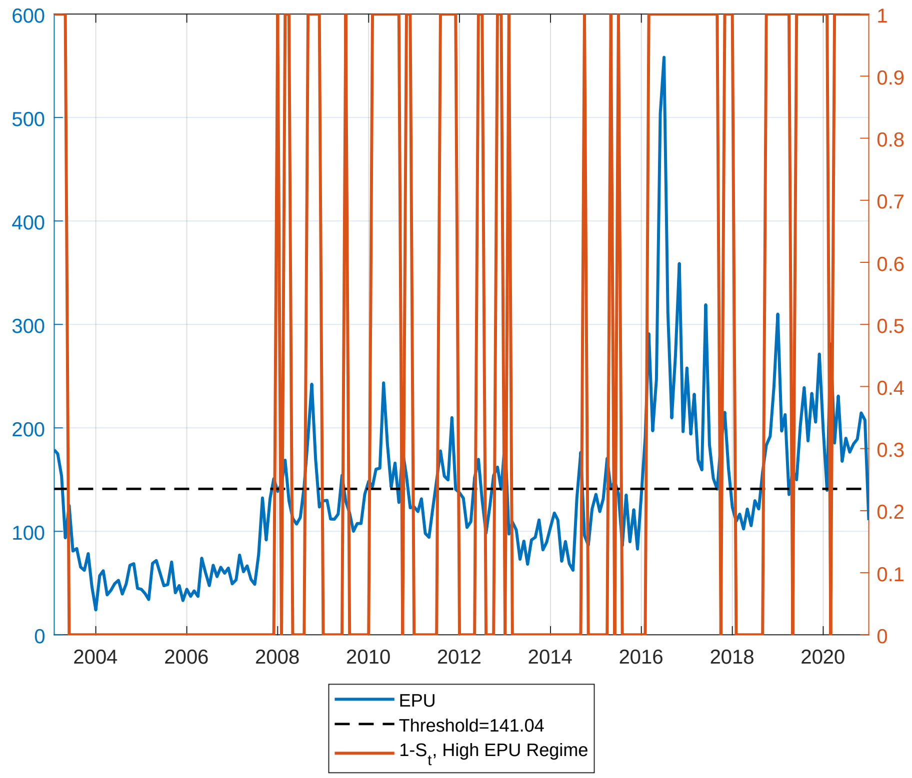

Figure 4: **UK Economic Policy Uncertainty Index, the Threshold Estimate, and High EPU Regime Periods**

Notes: This figure plots the UK Economic Policy Uncertainty Index of Baker et al. (2016) from February 2003 to January 2021 along with the posterior modal threshold estimate from the SVOL-IM-TVAR model, i.e. $Z^* = 141.04$, to be read in conjunction with the LHS axis. Note the posterior modal delay parameter d=1. We also plot periods of high EPU regimes, $(1 - S_t)$, against time to be read in conjunction with the RHS axis.

and the bottom row in the high EPU regime. A shock of this magnitude is comparable with the surge in EPU following the EU referendum result in June 2016. Overall, these results are similar to those in Figure 3, with the exception of GDP growth. For GDP growth, the error bands show that, on impact, it is difficult to determine how GDP responds. Inflation declines temporarily in both regimes, and financial stress temporarily surges. Divisia money growth declines in both regimes.

Importantly, there is very little difference in the transmission mechanism of EPU shocks across regimes. To investigate further, we plot the responses of economic variables to model-implied overall economic uncertainty, which corresponds to the stochastic volatility factor common to all variables in the system, in Figure 6. These plots reveal asymmetries in the response of all variables across high and low EPU regimes. In particular, within the high EPU regime, the surge in EPU is larger relative to the response in low EPU regime. Also notice that GDP growth and inflation decline on impact in the high EPU regime, but rise in the low EPU regime. Divisia money growth declines in both regimes, but the magnitude of the contraction is greater in the high EPU regime. Finally, regarding financial stress, the response is similar across both regimes.

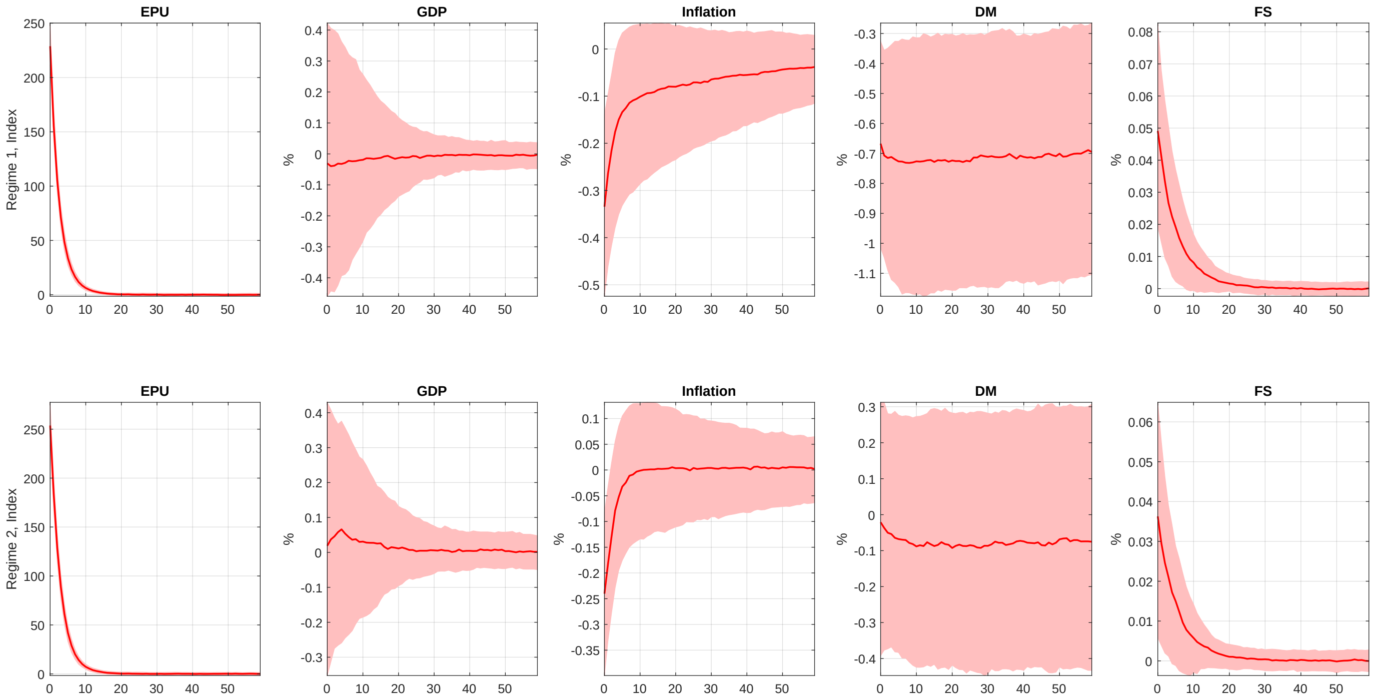

Figure 5: **Regime Specific Impulse Response Functions of UK Economic Variables with respect to an Economic Policy Uncertainty Shock from the SVOl-IM-TVAR Model**

Notes: This figure plots the impulse response functions of: economic policy uncertainty (EPU); GDP growth (GDP); CPI inflation (CPI); Divisia money growth (DM); and financial stress (FS), with respect to a five-standard deviation shock to economic policy uncertainty. The top row reports impulse response functions in the low EPU regime, and the bottom row plots impulse response functions in the high EPU regime. We plot the responses over a 60-month horizon. Shaded areas denote 68% error bounds.

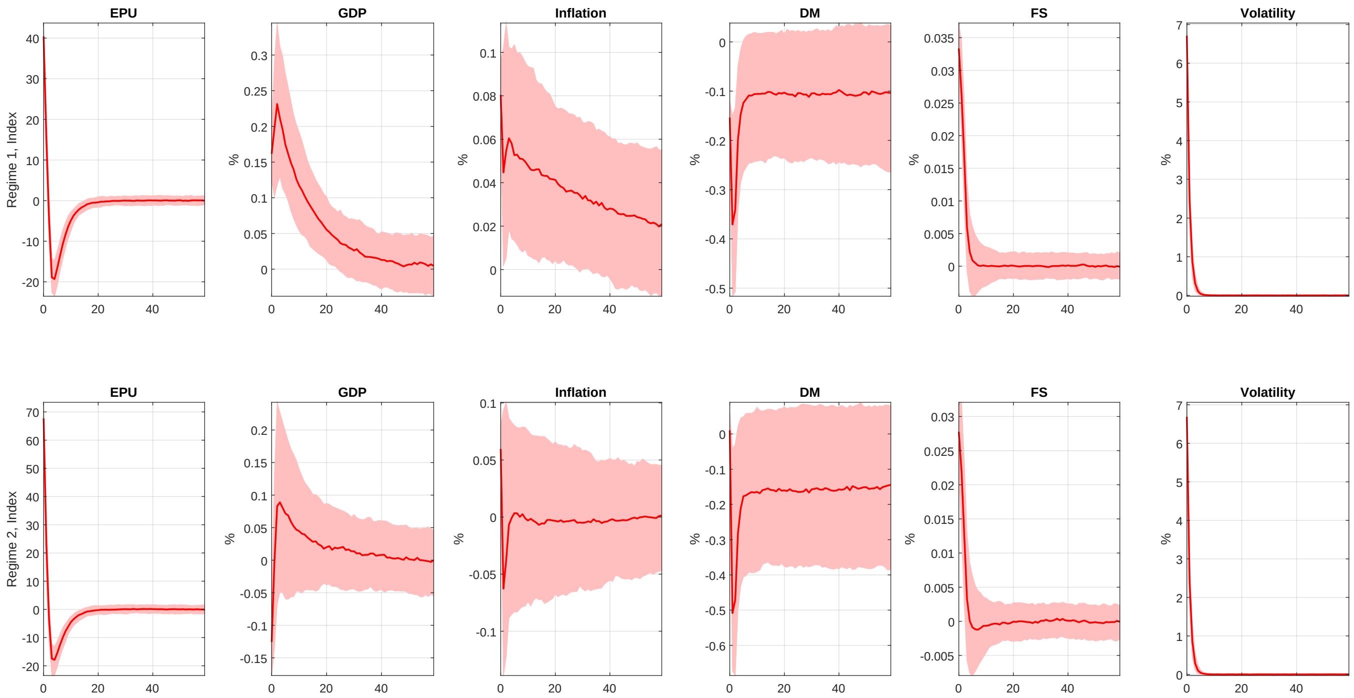

Figure 6: **Regime Specific Impulse Response Functions of UK Economic Variables with respect to Model-Implied Overall Economic Uncertainty Shocks from the SVOl-IM-TVAR Model**

Notes: This figure plots the impulse response functions of: economic policy uncertainty (EPU); GDP growth (GDP); CPI inflation (CPI); Divisia money growth (DM); and financial stress (FS), with respect to a five-standard deviation shock to model-implied economic uncertainty. The top row reports impulse response functions in the low EPU regime, and the bottom row plots impulse response functions in the high EPU regime. We plot the responses over a 60-month horizon. Shaded areas denote 68% error bounds.

These plots reveal that the transmission mechanisms of EPU shocks are similar across regimes. At the same time, the transmission mechanism of overall economic uncertainty shocks changes depending on whether the UK is in the high or low EPU regime. We posit two non-mutually exclusive reasons why we observe this. The first is due to the generalised nature of the impulse response functions we compute for the SVOL-IM-TVAR model. By definition, we allow for regime changes when simulating the responses and this may cause almost symmetrical responses to EPU shocks as well as the relatively indeterminate path of GDP growth. The second reason may be because the model allows for feedback effects of the stochastic volatility process that mute the impact of other shocks.

We now investigate the economic importance of EPU and overall economic uncertainty shocks using forecast error variance decompositions (FEVDs). Table 1 reports the posterior median and 95% posterior bands of the percent share of forecast error variance attributable to EPU shocks and overall economic uncertainty shocks at a 60-month horizon for each regime. Three key points emerge from Table 1. First, uncertainty shocks explain a higher proportion of macroeconomic and financial variation in the high EPU regime. Second, and more importantly, the FEVDs with respect to EPU shocks in the high EPU regime have a far lower degree of posterior uncertainty. Finally, EPU shocks explain a higher proportion of macroeconomic and financial variation in each respective regime.

Table 1: **Regime-Specific Percent Share of Forecast Error Variance Attributable to EPU and Overall Economic Uncertainty Shocks**
Notes: This table reports the posterior median of the percent share of forecast error variance attributable to economic policy uncertainty (EPU) shocks and overall model-implied economic uncertainty (UNC) shocks for UK economic variables at a 60-month horizon. The top half reports forecast error variance decompositions (FEVDs) in the low EPU regime and the bottom half reports analogous results for the high EPU regime. Square brackets contain the 2.50% and 97.5% quantiles of the posterior distribution. EPU is economic policy uncertainty, GDP is GDP growth, CPI is inflation, DM is Divisia money growth, and FS is the financial stress index.

	Low EPU Regime				
	EPU	GDP	CPI	DM	FS
EPU shocks	85.80	2.37	2.40	5.99	4.26
	[80.92 90.15]	[0.68 9.79]	[0.43 16.14]	[0.25 26.42]	[1.17 13.57]
UNC shocks	5.53	1.55	1.11	0.57	2.32
	[3.20 8.46]	[0.52 4.21]	[0.23 5.40]	[0.09 3.72]	[1.07 4.42]
	High EPU Regime				
	EPU	GDP	CPI	DM	FS
EPU shocks	81.27	2.53	2.05	1.30	3.40
	[75.72 85.81]	[0.77 7.45]	[0.42 11.63]	[0.17 9.22]	[1.16 9.93]
UNC shocks	7.88	1.85	1.33	0.85	2.44
	[5.52 11.10]	[0.58 5.70]	[0.24 7.64]	[0.13 7.08]	[1.26 5.13]

Our final result from the SVOL-IM-TVAR model provides a narrative on the historical role of shocks to overall economic uncertainty. We conduct a counterfactual analysis, in which shocks to the volatility process in Equation 9 are absent, $\eta_t = 0$. Here, the volatilities of all level shocks in the economy are constant at their respective sample means. We take each parameter draw from the posterior distribution and simulate the variables in the model under the counterfactual. We then take the difference between the actual data and the counterfactual scenario. The difference between the real and model-generated data informs us of the role overall economic uncertainty shocks have throughout our sample, or, equivalently, the loss of fit in assuming volatility remains constant.

We plot the difference between posterior median and 95% error bands for the difference between each variable and those we generate from our counterfactual scenario in Figure 7. For GDP growth, we can see that there are negligible differences between the observed data and those from our counterfactual. Focussing on 2020, we see positive deviations between real data and the counterfactual. This implies that in the absence of overall economic uncertainty shocks, the model slightly overestimates the contraction in GDP growth, although the real data still lies within the 95% bands of the posterior distribution of our GDP series under the counterfactual. Looking at CPI inflation and Divisia money, there are negligible differences, none of which are statistically significant. Finally, we note that in the absence of overall economic uncertainty shocks, financial stress would have been lower throughout 2020. This statistically significant difference implies a substantial spillover of economic conditions to financial markets. The existence of such spillover effects should be considered in the context of the Bank of England's actions immediately after the EU referendum[3] and after the announcement of the initial social distancing measures in March 2020.[4] On both occasions, the Bank stood ready to provide the financial system with substantial injections of additional liquidity and to consider further policy responses in order to alleviate the impact of the shock on the firms operating in the real economy.

Taken together, these results demonstrate considerable symmetries between transmission mechanisms from EPU shocks to economic variables across both the low and the high EPU regime. However, those symmetries across the two EPU regimes disappear once we investigate the responses of the economic variables to shocks to the model-implied overall economic uncertainty. Regarding the economic importance of these shocks, FEVDs show that EPU shocks explain a greater proportion of economic variation relative to overall economic uncertainty shocks in both regimes. Furthermore within the high EPU regime we obtain far more precise estimates of the proportion of variation attributable to EPU shocks relative to those in the low EPU regime. Our counterfactual analysis reveals that overall economic uncertainty shocks are important in driving financial conditions, particularly in the high EPU regime.

[3] Bank of England Governor Mark Carney's statement on 24 June 2016.

[4] HM Treasury and the Bank of England launch a Covid Corporate Financing Facility (CCFF).

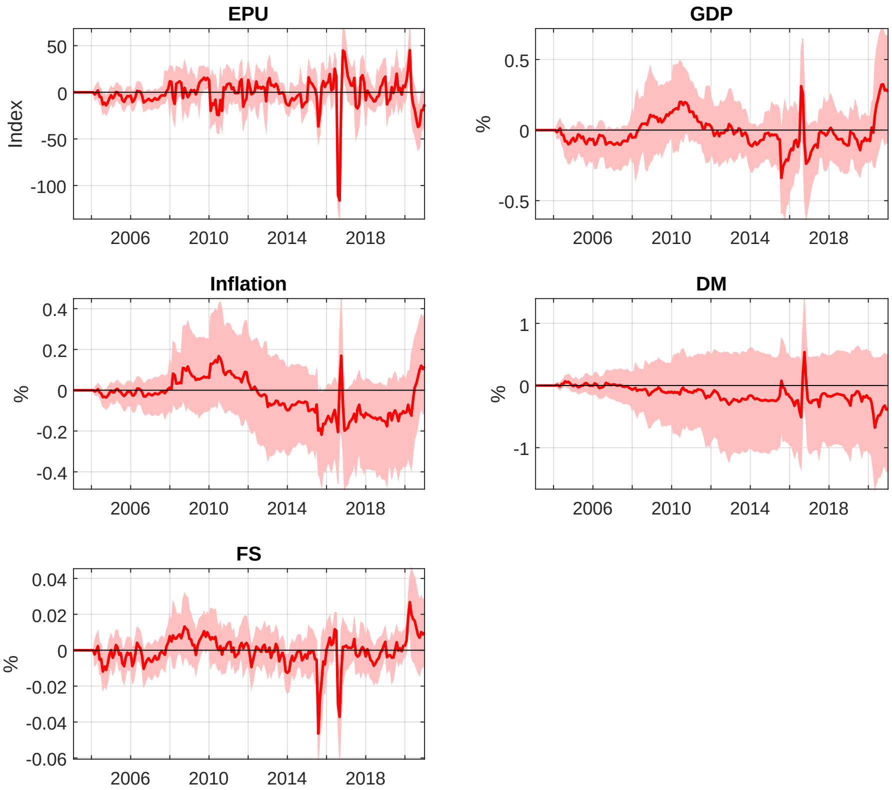

Figure 7: **Counterfactual without Uncertainty Shocks from February 2003 to January 2021**
Notes: This figure shows the difference between real data and model-implied data under the assumption of no volatility shocks (i.e. $\eta_t = 0$ in Equation 9). EPU is economic policy uncertainty, GDP is GDP growth, Inflation is CPI inflation, DM is Divisia money growth, and FS is the UK financial stress index. Solid lines denote the posterior median and shaded areas denote 95% error bounds. For ease of interpretation, we also provide a solid line at 0 for each plot.

4 Robustness checks

We carry out several additional tests in order to establish the robustness of the results we report.[5] First, we investigate alternative orderings of the linear Bayesian VAR using the Lenza and Primiceri (2020) adjustment. We obtain qualitatively similar impulse response functions to those we report in Section 3.1. Second, we add the infectious disease index available from https://www.policyuncertainty.com. This index is based on approximately 3,000 US newspaper articles that contain economic terms (such as 'economy' and 'financial'), stock market terms (such as 'stock market' and 'equity'), volatility terms (such as 'uncertainty' and 'risk'), and infectious disease terms (such as 'epidemic', 'pandemic', 'virus', 'flu' 'coronavirus', 'MERS' and 'SARS'). Although we find that shocks to the infectious disease variable cause a contraction in GDP growth, this

[5]All additional results are available upon request.

contraction is smaller than that caused by the shock to EPU. Impulse response functions of other variables are qualitatively similar to those we report above.

In our third robustness check, we estimate the SVOL-IM-TVAR model whilst restricting the sample to end in December 2019. Impulse response functions are almost identical to those we report above, as are the forecast error variance decompositions. Finally, we re-estimate the SVOL-IM-TVAR model but change the variable governing regime dynamics from the EPU index to the FS index. This alternative model distinguishes between periods of high and low financial stress. Our main conclusions regarding: i) impulse response analysis; ii) forecast error variance decompositions; and iii) the counterfactual experiment, are similar to our baseline specification.

5 Conclusion

The outbreak and the rapid spread of the COVID-19 pandemic has led to a series of substantial macroeconomic shocks across the world, which produce significant outliers in the time series of key indicators of interest to policymakers and other economic agents. This presents an important challenge from a macro-econometric standpoint, as the existence of such extreme observations in the data affects the reliability and the robustness of inferences drawn from standard models, such as vector autoregressions. Such issues are particularly pertinent in the context of the assessment of the economic effects of increased policy uncertainty following the United Kingdom's decision in June 2016 to leave the European Union and its eventual departure in December 2020.

We address this issue in this paper by estimating two Bayesian VAR models, which account for the aforementioned outliers in the data, and incorporate stochastic volatility and distinguish between high and low policy uncertainty regimes. This allows us to accurately examine the relationship between the UK economic policy uncertainty index and several macroeconomic and financial indicators, such as GDP growth, Divisia money growth, CPI inflation, and financial stress index.

Our results indicate that accounting for the outliers in the data brought by the COVID-19 pandemic allows for identification of an economically and statistically significant contractionary effect of economic policy uncertainty shocks on UK GDP growth. The impulse response functions we generate also show that Divisia money stimulus further facilitates GDP growth, while shocks to financial stress lead to long-lasting contractions in GDP.

Furthermore, our examination of the relation between economic policy uncertainty and the macroeconomic and financial variables of interest that accounts for whether the UK is in a low or a high EPU regime reveals a remarkable degree of symmetry of EPU shock transmission mechanisms in the two regimes. That being said, we do find marked differences across the two EPU regimes when we study shocks to a model-implied overall economic uncertainty variable instead. In particular, we establish that GDP growth and CPI inflation decline on impact in the high EPU regime, but increase in the low EPU regime.

Given the timing of the United Kingdom's departure from the European Union and the outbreak of the COVID-19 pandemic, it is not possible to isolate their individual economic effects from one another. Nevertheless, the results documented in this paper demonstrate the clear need for and the benefits of adequately accounting for the extreme outliers in macroeconomic and financial data when evaluating the impact of economic policy uncertainty on the real economy. This is particularly important for the purposes of policy design and evaluation, as we show that failure to account for such shocks reduces the ability of macroeconomic models to fully capture the impact of important policy events on key indicators of economic activity.

Appendix

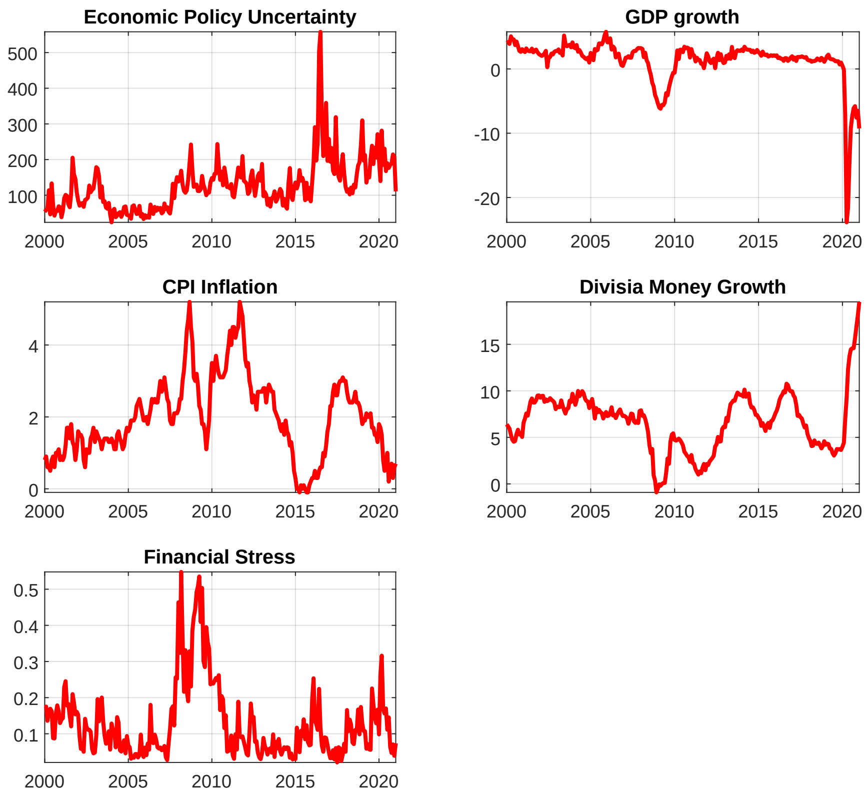

Figure 8: **UK Economic Data from Janaury 2000 to January 2021**
Notes: This figure plots the UK Economic Policy Uncertainty Index of Baker et al. (2016), annual GDP growth, annual CPI inflation, annual Divisia money growth and the UK's financial stress index from January 2000 to January 2021.

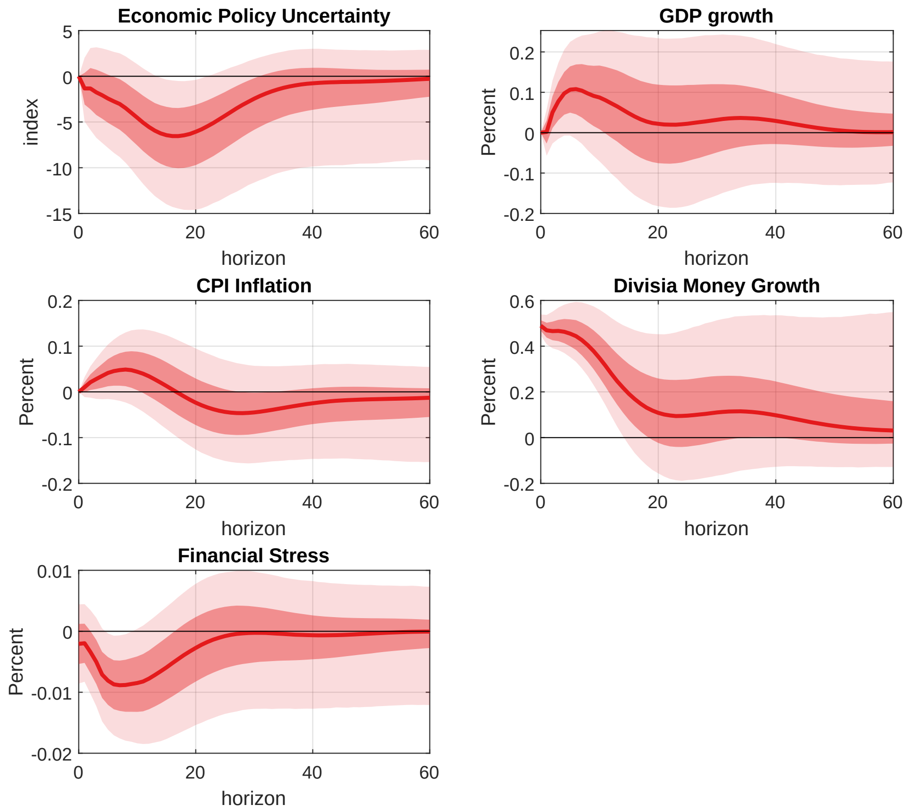

Figure 9: **Impulse Response Functions of UK Economic Variables with respect to a Divisia Money Shock from a Bayesian VAR with the Lenza and Primiceri (2020) Adjustment**

Notes: This figure plots the impulse response functions of: economic policy uncertainty (EPU); GDP growth (GDP); CPI inflation (CPI); Divisia money growth (DM); and financial stress (FS), with respect to a one-standard deviation shock to Divisia money growth. We plot the responses over a 60-month horizon. Dark (light) shaded areas denote 68% (95%) error bounds.

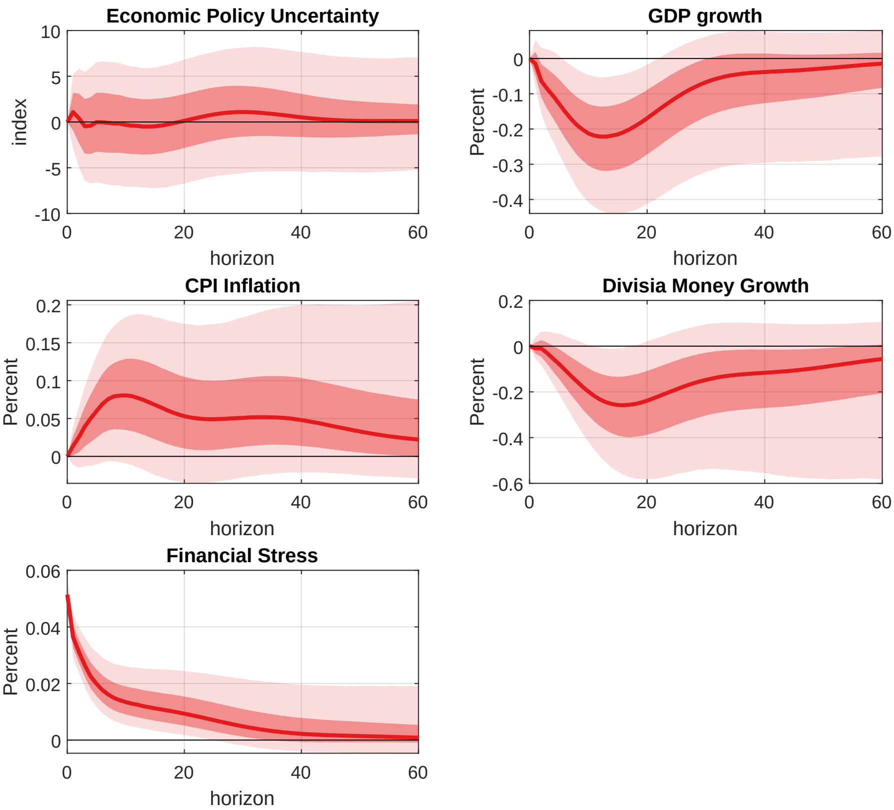

Figure 10: **Impulse Response Functions of UK Economic Variables with respect to a Financial Stress Shock from a Bayesian VAR with the Lenza and Primiceri (2020) Adjustment**

Notes: This figure plots the impulse response functions of: economic policy uncertainty (EPU); GDP growth (GDP); CPI inflation (CPI); Divisia money growth (DM); and financial stress (FS), with respect to a one-standard deviation shock to financial stress. We plot the responses over a 60-month horizon. Dark (light) shaded areas denote 68% (95%) error bounds.

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