Monetary Policy across Space and Time*

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Abstract

In this paper we ask two questions: (i) is the conduct of monetary policy stable across time and similar across major economies, and (ii) do policy decisions of major central banks have international spillover effects. To address these questions, we build on recent semi-parametric advances in time-varying parameter models that allow us to increase the VAR dimension and to jointly model three advanced economies (US, UK, and the Euro Area). Our main reduced-form finding is an increased connectedness between and within countries during the recent financial crisis. In order to study policy spillovers, we jointly identify three economy-specific monetary policy shocks using a combination of sign and magnitude restrictions. We find that monetary policy shocks were larger in magnitude and more persistent in the early 1980s than in subsequent periods. We also uncover positive spillover effects of policy between countries in the 1980s and diminished, and sometimes negative 'beggar-thy-neighbour' effects in the second half of the sample. Moreover, during the 1980s, we find evidence for policy coordination between central banks.

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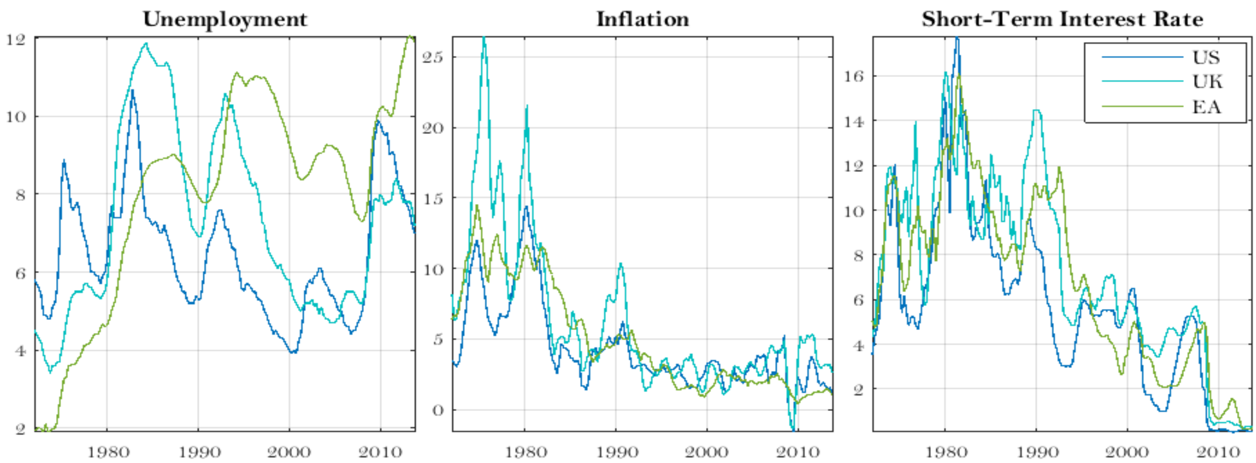
1 Introduction

The past 50 years have seen three major economic events that have been shared across many industrialized economies: the Great Inflation of the late 1970s and early 1980s, the Great Moderation starting in the mid-1980s, and the 2008 financial crisis and the subsequent recession. In this paper we use macroeconomic time series for three major world economies (the Euro Area, the US, and the UK) that feature these key events as a backdrop to ask what the conduct and effects of monetary policy have been, how they have changed over time, and whether they have been similar across these economies. A question of particular importance for monetary policy concerns policy spillovers: do macroeconomic variables in major economies react to decisions of central banks in other major economies? Our choice of countries is motivated by the fact that the selected economies account for more than a third of total world GDP. Even though they all share the historic episodes mentioned before, the magnitude of these events has been dramatically different, as illustrated in Figure 1: the Great Inflation was most severe in the UK, while the Bundesbank, which later joined the European Central Bank (ECB), is often credited with avoiding the large spikes in inflation we have seen in the other two countries. The Great Moderation period, characterized by low and stable inflation and unemployment, arrived later in the UK than in the US. Finally, the recession after the recent financial crisis and the associated recovery followed a very different path in the Euro Area (EA).

In this paper, we estimate a time-varying parameter model with drifting volatility using a semi-parametric approach to investigate monetary policy experiences across countries and during the three major events described above. We jointly identify three economy-specific monetary policy shocks and investigate the spillover effects of policy across countries and time. To this end, we employ a combination of sign and magnitude restrictions, leaving most variables' responses unrestricted, and letting the data speak on their direction and size.

The motivation behind our modeling choice is that vector autoregressive (VAR) models are well-suited for answering our research questions, as they allow for modeling interconnectedness and joint dynamics of macroeconomic time series. However, ignoring the structural changes and breaks in the past few decades that are both evident in the data and documented in the literature, can result in invalid inference; hence, allowing for time-variation in the parameters and volatility of the VAR model is essential. Because of the multi-country connections we want to explore, we also require a relatively large number of observables in the VAR model alongside parameter drift.

Figure 1: Unemployment, Inflation and Interest Rates across countries



Time-varying parameter (TVP) VAR models have been made popular by Cogley and Sargent (2005) and Primiceri (2005). One concern of the model specification popularized in these papers is that it is generally not amenable to having more than a few variables in the VAR (the upper bound in the literature seems to be around five, as used, for example, in Amir-Ahmadi, Matthes and Wang (2016)) and few lags (the standard choice seems to be two lags for quarterly data, as in Cogley and Sargent (2005) and Primiceri (2005)). The reason for this concern is that state space methods used to filter the drifts in the parameters are subject to the 'curse of dimensionality' which is particularly severe when considering richly parameterized VAR models. This prevents researchers from using larger datasets that have been employed and found important in fixed-coefficient VARs (see, for example, Christiano, Eichenbaum and Evans (1999)).

To handle a larger number of drifting parameters, we use the quasi-Bayesian local likelihood approach to estimate time-varying parameter VARs introduced in Petrova (2018). The combination of the closed-form quasi-posterior expressions derived in Petrova (2018) with standard Minnesota-type priors used in the literature on fixed-coefficient VARs specified directly on the drifting parameters, allows the number of variables in the VAR to be large while also facilitating the parameter drift. Moreover, the quasi-Bayesian local likelihood approach of Petrova (2018) models the parameter time-variation nonparametrically, ensuring consistent estimation in a wide class of parameter processes and alleviating the risk of invalid inference due to misspecifying the state equations for the latent parameters in random coefficient models. Finally, the availability of analytic expressions for the quasi-posterior density in the Gaussian VAR case eliminates the computational burden of

Markov chain Monte Carlo (MCMC) algorithms used for the estimation of TVP VARs by state space methods, making the proposed quasi-Bayesian procedure simple and computationally fast.

Our main empirical results are organized in two parts. First, we compute various reduced-form quantities that help us understand the similarities and differences between the three economies we study: we use our VAR to estimate standard quantities such as trends, gaps, volatilities, correlations, persistence measures, and a reduced-form view of the Phillips curve trade-off in each economy. Furthermore, we build on recent advances in analyzing network structures using VAR estimates, such as Diebold and Yilmaz (2014), and show how the connectedness between variables has changed over time.

Second, we identify the effects of monetary policy shocks originating in each of the three economies using a combination of sign restrictions (as popularized by Faust (1998), Canova and Nicolo (2002), and Uhlig (2005)) and magnitude restrictions (De Graeve and Karas (2010)). These magnitude restrictions can substantially help with identification, as recently emphasized by Amir-Ahmadi and Drautzburg (2017). Identifying a monetary policy shock serves two purposes in this paper: (i) we can compare the size of monetary policy surprise shocks and their domestic effects over time and across countries, and (ii) we ask how an economy's key variables react to unexpected policy changes by other central banks. The latter results can also be used to study the question coordination between central banks, a topic which we devote some attention to.

There is a vast literature on monetary policy coordination and the associated welfare effects, studied through a game theoretic framework (for example, Canzoneri and Gray (1985), Clarida, Gali and Gertler (2002), Corsetti and Pesenti (2005), Gali and Monacelli (2005), Benigno and Benigno (2006), and Coenen, Lombardo, Smets and Straub (2007)). This literature suggests that policy cooperation generally has some welfare gains as opposed to non-coordination or implementing an exchange rate peg, but it can sometimes generate incentives for central banks to 'cheat' and deviate from commitments. Moreover, the results differ depending on the relative size of the economies considered (i.e., if the game is symmetric) as well as on whether players move simultaneously and whether the game is played repeatedly. There is also a long-standing literature on the international effects of monetary policy in the absence of policy coordination. Most papers in the literature extend the classic static Mundell-Fleming-Dornbusch model to include dynamics, intertemporal preferences and various frictions. The conclusions in the literature differ considerably with some papers predicting negative 'beggar-thy-neighbour' effects on foreign variables by domestic monetary policy (Mundell (1963)), some finding off-setting effects (Obstfeld and Rogoff (1995)), while others predicting positive 'complementary' spillover effects (Corsetti and Pesenti (2001)). The results in the literature are largely determined by the relative strength of the different transmission channels of monetary policy (exchange rate, terms of trade, or current account channels) imposed through the theoretical assumptions as well as the parameter calibrations of the models in these papers.

Because there is a lack of clear consensus in the literature on the direction of policy spillover effects and coordination of monetary policy, our approach is useful as it imposes fewer theoretical restrictions and lets the data speak, while also allowing for the possibility that these effects might be changing over time.

The empirical macroeconomic literature that has touched upon some of our research questions includes Lubik and Schorfheide (2006), Gerko and Rey (2017), Stephane, Pesaran, Smith and Smith (2013), to name a few. For example, Gerko and Rey (2017) compare the effects of monetary policy shocks across the UK and US and find that the spillover effects are stronger from the US to the UK than vice versa. Gerko and Rey (2017) are silent on how these effects have varied over time, a focus of our paper. Papers that study how much co-movement there is across major economies include Canova, Ciccarelli and Ortega (2007) and Billio, Casarin, Ravazzolo and Van Dijk (2016). The latter studies a sample that includes the financial crisis and finds, similar to our results, stronger co-movement in that period compared to earlier periods (focusing on the US and the EA only). Concerning monetary policy, some papers have analyzed differences in the 1970s: DiCecio and Nelson (2009) emphasize similarities between the conduct of US and UK monetary policy in the 1970s, whereas Beyer, Gaspar, Gerberding and Issing (2008) emphasize large differences in estimated policy rules between the US, UK, and Germany during that period. Most of the empirical literature either estimates a fixed-parameter VAR or DSGE model, typically considering a smaller subset of the sample to avoid estimation bias stemming from the structural change in the series, or estimates a time-varying model either through considering a small number of variables, possibly at the cost of omitted variable bias, or by imposing some additional (factor/ Markov-switching) structure on the parameter time-variation. The advantage of our approach is that we model jointly the three economies using a larger variable set and longer sample, while also allowing for time-variation in the dynamics of all variables.

Our main reduced-form result is that once we allow for drifts in the model's parameters, we find significant time-variation in the cross-country interconnectedness, based on weighted directed networks constructed as in Diebold and Yilmaz (2014). Particularly, connectedness of economic and financial variables within and between countries is smaller during the Great Moderation and increases considerably during the recent financial crisis, making spillover from financial to real variables as well as cross-country contagion much more severe. Our monetary policy shock analysis suggests several conclusions. First, monetary policy shocks are larger in magnitude and more persistent in the Great Moderation than in any subsequent periods in all economies. Second, we find positive spillover effects of policy across countries in the 1980s (particularly from the EA to US and UK, as well as from US to UK and from UK to US) as well as evidence for policy coordination during that period, and smaller and sometimes negative 'beggar-thy-neighbour' spillover effects and no coordination in the subsequent periods. Third, while we impose that the effects of foreign monetary policy shocks are smaller on impact than domestic policy shocks, foreign spillovers can occasionally have more persistent effects.

The remainder of the paper is organized as follows. Section 2 outlines the Bayesian semi-parametric methodology utilized in the paper and provides a brief comparison with alternative methods. Section 3.1 contains a detailed description of the model specification, data, and priors. Sections 3.2 and 3.3 present the reduced-form empirical results and Section 3.4 contains the structural shock analysis of the paper. Finally, Section 4 concludes, and the supplementary Appendix contains additional results.

2 Methodology

In this section, we outline the quasi-Bayesian local likelihood (QBLL) methodology developed for reduced-form VAR models in Petrova (2018). Before going into the technical details, we want to emphasize four major advantages of this approach.

The first advantage is a remedy for the 'curse of dimensionality' problem. The standard approach to estimating time-varying parameter VARs with stochastic volatility involves casting these models in state space form (Cogley and Sargent (2002, 2005), Primiceri (2005)) and exploiting the MCMC algorithms for approximation of the posterior of the parameters (states). The most serious limitation to the practical use of this state space appoach to TVP VAR models is its inability to accommodate larger systems. The size and complexity of the state space increases with the VAR dimension, since an extra state equation is required for each parameter as well as an additional shock and additional coefficients[1]. As a result, state space methods are subject to the

[1] In a state space setting, an M-dimensional TVP VAR (k) with stochastic volatility requires the addition of $M(3/2+M(k+1/2))$ state equations, so for instance, a simple five variable TVP VAR(4) requires 120 state equations.

'curse of dimensionality' and their application to the estimation of TVP VAR models is limited to a model of four to five variables. This makes the use of the standard approach infeasible for our application. Additional estimation complexity of state space models arises from the use of MCMC algorithms. On the other hand, the QBLL methodology employed in this paper admits a closed-form quasi-posterior density, facilitating estimation of large VAR systems. For example, Petrova (2018) estimates an 80-variable VAR model with time-variation in the parameters and the covariance matrix in a little over a minute of computation time. Such a model in a state space setup would require 9,720 state equations just to allow for a single lag, which is clearly infeasible. An alternative to our approach would be to assume more structure on the VAR coefficients or the volatilities; for example, a factor structure, as outlined by Canova and Ciccarelli (2009), Canova and Sala (2009), Amisano, Giannone and Lenza (2015), or a panel structure as in Koop and Korobilis (2018) or Canova et al. (2007). Our methodology does not require imposing such constraints a priori, which can be restrictive and even invalid if the model does not obey the assumed structure. Additionally, choosing prior distributions in models with a factor structure in the coefficients can be burdensome.

The second advantage of our methodology is that the standard state space approach is fully parametric and thus requires a parametric law of motion for the drifting parameters, with a random walk process being the most common assumption in the literature (see for example, Cogley and Sargent (2002, 2005), Primiceri (2005), Mumtaz and Surico (2009), Cogley, Primiceri and Sargent (2010) and Clark (2012)). While convenient, this assumption is restrictive and can provide invalid inference even asymptotically if the true law of motion is misspecified. On the other hand, our methodology is nonparametric with respect to the parameter time-variation and as a result valid in a wide class of deterministic and stochastic processes (see Petrova (2018) for further discussion and Monte Carlo evidence using various data-generating processes).

Third, to maintain symmetry and positive definiteness of the drifting reduced-form covariance matrix, state space methods resort to diagonalization, e.g. Cogley and Sargent (2005), Primiceri (2005), Cogley et al. (2010) use Cholesky decomposition assuming that the diagonal elements follow a random walk in logarithms. This implies that the ordering of the variables in the VAR matters for inference[2], which can be undesirable particularly for reduced-form analysis. The QBLL approach permits direct estimation of the time-varying covariance matrix, which has a time-varying inverted-Wishart posterior density, remaining by construction symmetric and positive definite at each point

[2]For a recent alternative parametric state space setup that does not share this problem, see Bognanni (2018).

in time.

Finally, as will become evident below, our approach permits the use of exactly the same priors that have been well-designed and used by researchers for many years for *fixed-coefficient* VARs. This makes prior elicitation substantially more straightforward than in the state space setup; for example, we do not have to rely on a training sample to obtain priors or starting values of the Kalman filter, which is standard when using fully parametric TVP VAR models. Note that this does *not* mean that we are restricted to standard priors coming from fixed-coefficient VARs. Our setup can accommodate flexible non-conjugate priors that can even facilitate time-varying prior beliefs.

We now turn to a more formal description of our model and the estimation algorithm. Let an $M \times 1$ dimensional vector y_t be generated by a stable time-varying parameter (TVP) heteroskedastic VAR model of lag order k:

$$y_t = B_{0t} + \sum\nolimits_{p=1}^{k} B_{pt} y_{t-p} + \varepsilon_t, \quad \varepsilon_t = \Gamma_t^{-1/2} \eta_t, \quad \eta_t \sim NID(0, I_M) \tag{1}$$

where B_{0t} is a vector of time-varying intercepts, B_{pt} are time-varying autoregressive matrices with all roots of the polynomial $\psi(z) = \det\left(I_M - \sum_{p=1}^{k} z^p B_{pt}\right)$ outside the unit circle, and Γ_t^{-1} a positive definite time-varying covariance matrix. Letting $x_t = (1, y_{t-1}', ..., y_{t-k}')$ and $B_t = (B_{0t}, B_{1t}, ..., B_{kt})$, the model (1) can be written as

$$y_t = (I_M \otimes x_t)\beta_t + \Gamma_t^{-1/2} \eta_t, \tag{2}$$

where $\beta_t := vec(B_t')$ is an $M(Mk+1) \times 1$ vector for each $t = 1, ..., T$. Further, define the matrices $Y = (y_1, ..., y_T)'$, $E = (\varepsilon_1, ..., \varepsilon_T)'$, $X = (x_1', ..., x_T')'$, and denote their vectorized forms by $y = vec(Y)$ and $\varepsilon = vec(E)$.

In order to estimate the time-varying parameters β_t and Γ_t, we employ a quasi-Bayesian methodology proposed by Petrova (2018), which builds on previous frequentist work by Giraitis, Kapetanios and Yates (2014). This class of semi-parametric estimators can handle both deterministic and stochastic time-variation and can provide valid inference for a wide class of models (see Giraitis et al. (2014) and Petrova (2018) for more details). For completeness, we include the conditions from these papers, sufficient for consistency and asymptotic normality of the time-varying parameter vector $\theta_t := \left[\beta_t, \left(vech\left(\Gamma_t^{-1}\right)\right)'\right]'$ below:

(i) θ_t is a deterministic process

$$\theta_t = f(t/T), \tag{3}$$

where $f(.)$ is a piecewise differentiable function or

(ii) θ_t is a stochastic process satisfying:

$$\sup_{j:|j-t|\leq h} ||\theta_t - \theta_j||^2 = O_p\left(h/t\right) \quad \text{for} \quad 1 \leq h \leq t \quad \text{as} \quad t \to \infty. \tag{4}$$

Petrova (2018) proves that in the Bayesian setup the resulting quasi-posterior distributions are asymptotically valid for inference and confidence interval construction in a general nonlinear likelihood setup. The intuition for this result is that the parameter vector θ_t is assumed to vary slowly enough through (3) and (4) to permit consistent estimation. Petrova (2018) also verifies that the required high-level assumptions are satisfied for the special case of a time-varying (but otherwise linear) Gaussian model, for which a closed-form time-varying Normal-Wishart expression for the quasi-posterior density is provided. In particular, the method requires introducing a reweighting of the likelihoods of the observations $(y_1, ..., y_T)$ for the VAR(k) model (1). This weighting function gives greater weight to observations in the vicinity of the time period whose parameter values are of interest. The resulting local likelihood function at each point in time j is given by

$$L_j(y|\beta_j, \Gamma_j, X) = (2\pi)^{-M\varkappa_{Tj}/2} \left|\Gamma_j\right|^{\varkappa_{Tj}/2} e^{-\frac{1}{2}\sum_{t=1}^{T}\vartheta_{jt}(y_t-(I_M\otimes x_t)\beta_j)'\Gamma_j(y_t-(I_M\otimes x_t)\beta_j)} \tag{5}$$

where the weights ϑ_{jt} are computed using a kernel function and normalized in the following way

$$\vartheta_{jt} = \varkappa_{Tj} w_{jt} / \textstyle\sum_{t=1}^{T} w_{jt}, \quad w_{jt} = K\left(\dfrac{j-t}{H}\right) \quad \text{for} \quad j, t \in \{1, ..., T\},$$

where $\varkappa_{Tj} := \left(\sum_{t=1}^{T}\left[w_{jt}^2 / \left(\sum_{t=1}^{T} w_{jt}\right)^2\right]\right)^{-1}$. The kernel function K is assumed to be a non-negative, continuous, and bounded function with a bandwidth parameter H satisfying $H \to \infty$ and $H = o(T/\log T)$. The rate of convergence is given by $\varkappa_{Tj}$, which behaves like H, implying a nonparametric rate; this is unsurprising, since we have an infinite sequence of parameter vectors to estimate. For example, the widely used Normal kernel weights are given by

$$w_{jt} = (1/\sqrt{2\pi})\exp((-1/2)((j-t)/H)^2) \quad \text{for} \quad j, t \in \{1, ..., T\},$$

while the rolling-window procedure results as a special case of the choice of a flat kernel weights: $w_{jt} = \mathbb{I}(\,|t-j| \leq H)$ for $j, t \in \{1, ..., T\}$. The weighted likelihood (5) can be written more compactly as

$$L_j(y|\beta_j, \Gamma_j, X) \propto \left|\Gamma_j\right|^{tr(D_j)/2} \exp\left\{-\frac{1}{2}(y - (I_M \otimes X)\beta_j)'(\Gamma_j \otimes D_j)(y - (I_M \otimes X)\beta_j)\right\} \tag{6}$$

where $D_j := diag(\vartheta_{j1}, ..., \vartheta_{jT})$ for $j \in \{1..., T\}$. The intuition behind what the kernel effectively achieves when we estimate the parameters at time j is to give more weight to observations close to the specific point in time j and down-weigh distant observations.

Next, we assume a Normal-Wishart prior distribution for β_j and Γ_j for $j \in \{1, ..., T\}$:

$$\beta_j|\Gamma_j \sim \mathcal{N}\left(\beta_{0j}, (\Gamma_j \otimes \kappa_{0j})^{-1}\right), \quad \Gamma_j \sim W(\alpha_{0j}, \gamma_{0j}) \tag{7}$$

where β_{0j} is a vector of prior means, κ_{0j} is a positive definite matrix, α_{0j} is a scalar scale parameter of the Wishart distribution, and γ_{0j} is a positive definite matrix. Then, by Proposition 2 of Petrova (2018), combining this prior with the weighted likelihood L_j in (6) delivers a Normal-Wishart quasi-posterior distribution for β_j and Γ_j for $j = \{1, ..., T\}$:

$$\beta_j|\Gamma_j, X, Y \sim \mathcal{N}\left(\widetilde{\beta}_j, (\Gamma_j \otimes \widetilde{\kappa}_j)^{-1}\right), \quad \Gamma_j \sim \mathcal{W}(\widetilde{\alpha}_j, \widetilde{\gamma}_j), \tag{8}$$

with posterior parameters:

$$\begin{aligned} \widetilde{\beta}_j &= \left(I_M \otimes \widetilde{\kappa}_j^{-1}\right)\left[(I_M \otimes X'D_jX)\hat{\beta}_j + (I_M \otimes \kappa_{0j})\beta_{0j}\right], \qquad (9)\\ \widetilde{\kappa}_j &= \kappa_{0j} + X'D_jX, \quad \widetilde{\alpha}_j = \alpha_{0j} + \sum\nolimits_{t=1}^{T}\vartheta_{jt}, \ \widetilde{\gamma}_j = \gamma_{0j} + Y'D_jY + B_{0j}\kappa_{0j}B_{0j}' - \widetilde{B}_j\widetilde{\kappa}_j\widetilde{B}_j', \end{aligned}$$

where

$$\hat{\beta}_j = (I_M \otimes X'D_jX)^{-1}(I_M \otimes X'D_j)y \tag{10}$$

is the frequentist local likelihood estimator of Giraitis et al. (2014) for β_j. Note that to generate a draw for the parameters at any point in time, we just need to draw from a conjugate Normal-Wishart posterior, which is very fast even for large systems. Thus, the main advantages of our approach over the standard fully parametric state space-based methods are its simplicity, computational efficiency and robustness to misspecification.

3 Empirical Application

3.1 Data and Priors

We employ quarterly data starting in 1971Q1 until 2013Q4 on the unemployment rate, the short-term nominal interest rate[3], the long-term (10-year) nominal interest rate on government bonds, year-on-year inflation (CPI-based for the US and EA, RPI-based for the UK), the annual growth

[3] We consider the short-term interest rate as the main policy instrument.

rate of an exchange rate index for each country trade-weighted against a basket of currencies, and the annual growth rate of a stock price index[4] for each country (S&P 500 for the US, DAX to proxy for the EA, and an all-share index for the UK from the Global Financial Database). For the pre-euro period of our sample, we follow the literature and use synthetic EA data constructed by Fagan, Henry and Mestre (2001) as a composite from individual countries' data series. The price indices for the inflation calculations and the unemployment rates are seasonally adjusted. Finally, to account for movements in commodity prices, we also add a series on global commodity price inflation computed as the annual growth rate of the Moody's commodity price index. For the estimation of our model, we use four lags and a Minnesota-style prior with overall shrinkage $\lambda = 0.05$. Since our VAR does not include variables with a clear stochastic trend, we follow standard practice (e.g., Bańbura, Giannone and Reichlin (2010) and Kilian and Luetkepohl (2017)) and center the coefficient on the first lag of each variable at zero. We also impose that at each point in time, the companion form of our VAR has only eigenvalues less than one in absolute value. The prior for the Wishart parameters is set following Kadiyala and Karlsson (1997).

We have performed a number of robustness checks and the main results in this section do not change. Some of these additional results can be found in the supplementary Appendix; the rest are available upon request. First, our results are robust to different values of the overall shrinkage parameter $\lambda = 0.01$, 0.3, 0.5, as well as lag orders of two, six, and eight quarters. In addition, our main results do not change when we replace EA data with German data (these additional results can be found in the supplementary Appendix). While the German data have the advantage that EA data aggregate various monetary policymakers into one artificial policymaker before the introduction of the euro, the EA data have the advantage over German data since the Bundesbank is not the sole decision-maker on German monetary policy after the introduction of the euro in 1999. These differences are not important in practice since the EA and German series are highly correlated for most of our sample, and our robustness check in the Appendix confirms this. Particularly, even before the advent of the euro, the Bundesbank had been a de facto leader in European policymaking decision (as emphasized by di Giovanni, McCrary and von Wachter (2009)). Conversely, the ECB has reacted, at least during its first years, strongly to German data (most likely to obtain a similar reputation to the Bundesbank), as highlighted in Alesina, Blanchard, Gali, Giavazzi and Uhlig (2001).

[4] We will henceforth refer to this growth rate of stock indices as stock returns, but it useful to remember that we do not explicitly take into account dividends.

3.2 Reduced-Form Evidence

We now present reduced-form evidence from our TVP VAR model. These following three subsections serve three purposes; we want to assess: (i) the differences in the economic environments in the US, UK, and EA, (ii) whether these economies have become more similar (and more interconnected in a sense we will make precise below), and (iii) how similar the conduct of monetary policy is across these economies. Perhaps surprisingly, even without taking a stand on the identification of a monetary policy, we can already glean some insights on both long-run differences across countries and on the monetary policy stance (i.e. how tight monetary policy is in each country). Before we proceed to actual results, it is worth pointing out how our estimated parameters vary over time. In the supplementary Appendix, we show that the estimated parameter paths behave similarly to random walks with drifts, which is in line with the parametric assumption made in the bulk of the previous literature on TVP VAR models. Thus, our findings are not driven by an estimated parameter variation that is at odds with existing literature.

To introduce the objects of our analysis, it will be useful for us to work with the companion form of the VAR model in equation (1):

$$z_t = \mu_t + A_t z_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \Omega_t), \tag{11}$$

$$z_t := \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}, \; \mu_t := \begin{bmatrix} B_{0t} \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \; A_t := \begin{bmatrix} B_{1t} & B_{2t} & \cdots & B_{pt} \\ I_M & 0 & \cdots & 0 \\ \vdots & \ddots & & \vdots \\ 0 & & I_M & 0 \end{bmatrix}, \; \eta_t := \begin{bmatrix} \varepsilon_t \\ 0 \\ 0 \\ 0 \end{bmatrix}.$$

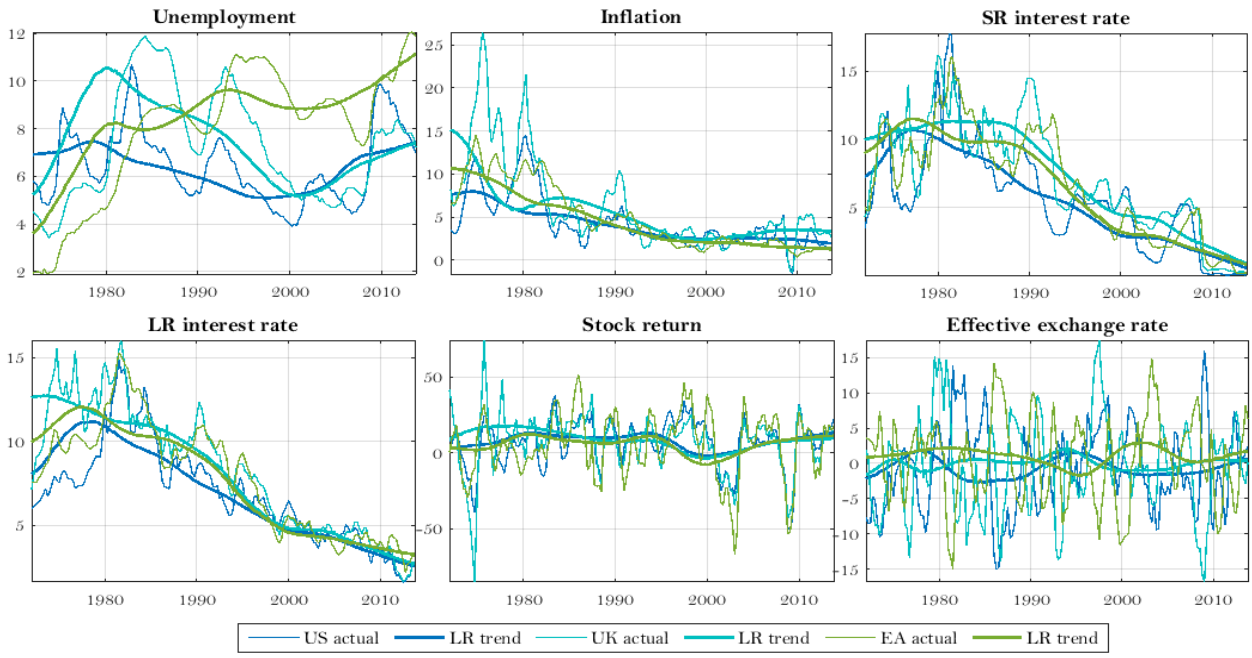
Because of the stability condition on the roots of the polynomial $\psi(z) = \det\left(I_M - \sum_{p=1}^{k} z^p B_{pt}\right)$, it follows that $\rho(A_t) < 1$, where $\rho(\cdot)$ denotes the spectral radius. One additional advantage of our econometric approach over the state space approach of Cogley and Sargent (2005) to TVP VAR models is that given the stability condition above and the assumed time-variation of the parameters in conditions (3) and (4), Giraitis, Kapetanios and Yates (2018) show that the TVP VAR model in (11) can be approximated by an vector MA(∞) process of the form

$$z_t = (I_{Mk} - A_t)^{-1}\mu_t + \sum_{h=0}^{\infty} A_t^h \eta_{t-h} + o_p(1). \tag{12}$$

For the reduced-form results in this section, we make use of this approximation[5] to compute the

[5] In the absence of such an approximation for state space models, the way the computation in (13) has been justified in the literature is via an 'anticipated utility approximation', i.e. assuming that parameters will not change in the future.

Figure 2: Actual series and their long-run trends



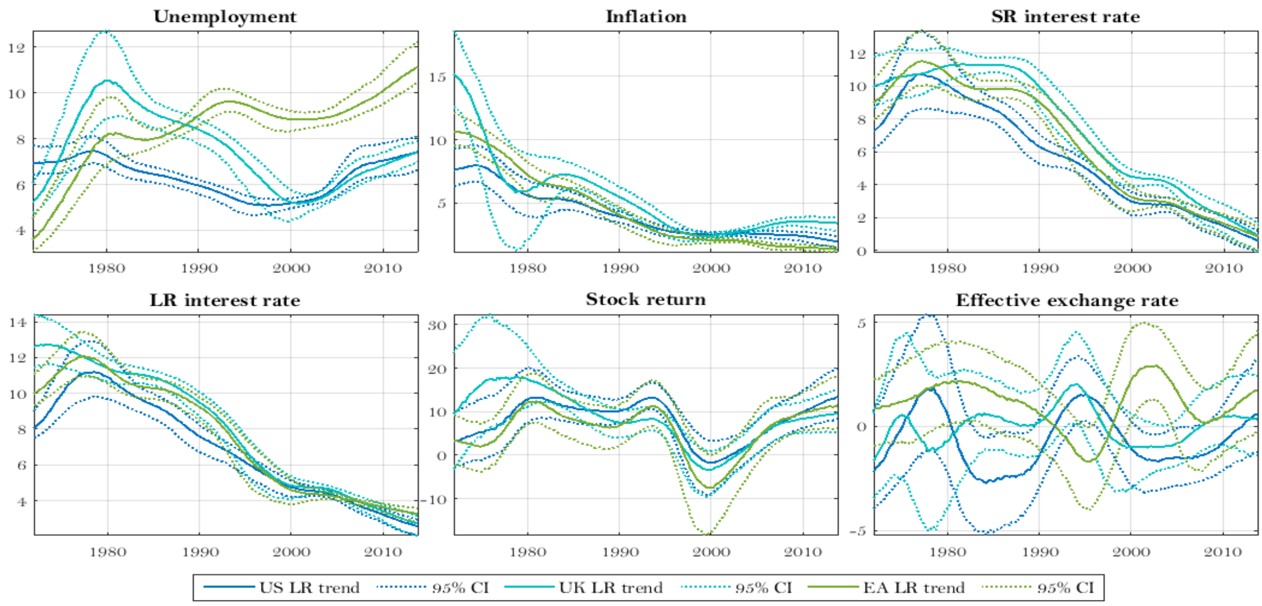
implied trends of the model's variables:

$$\tau_t = (I - A_t)^{-1}\mu_t. \tag{13}$$

The first M elements of τ_t can be interpreted as long-run economic expectations or infinite horizon forecasts implied by the model $\tau_t = \lim_{h\to\infty} \mathbb{E}\left(z_{t+h}|\mathcal{F}_t\right)$ and have been used by Cogley and Sargent (2005) to study changes in 'core' or 'natural' rates. The approach is closely related to the notion of an infinite horizon forecast as a trend embedded in the Beveridge-Nelson approach.

We estimate the quasi-posterior of these trends using the quasi-posterior of the model's parameters in (8) and, in Figure 2, we study how they have evolved over time. Figure 2 compares the actual series with the fitted long-run means, i.e. the posterior median of τ_t, (in bold lines), computed using equation (13), and Figure 3 presents their implied 95% posterior posterior intervals. In terms of trends, it turns out that both for short-run and long-run nominal interest rates, the trends are very similar across economies at the end of the sample. If we interpret the short-term interest rate as the policy instrument of the central bank, this means that any major recent differences across monetary policies in the three economies we study must be at higher frequencies. The trends in the short-term interest rates were also similar in the mid-1970s, with big differences only emerging in the 1980s. Unsurprisingly, stock return trends are also very similar across economies. The most

Figure 3: Long-run trends

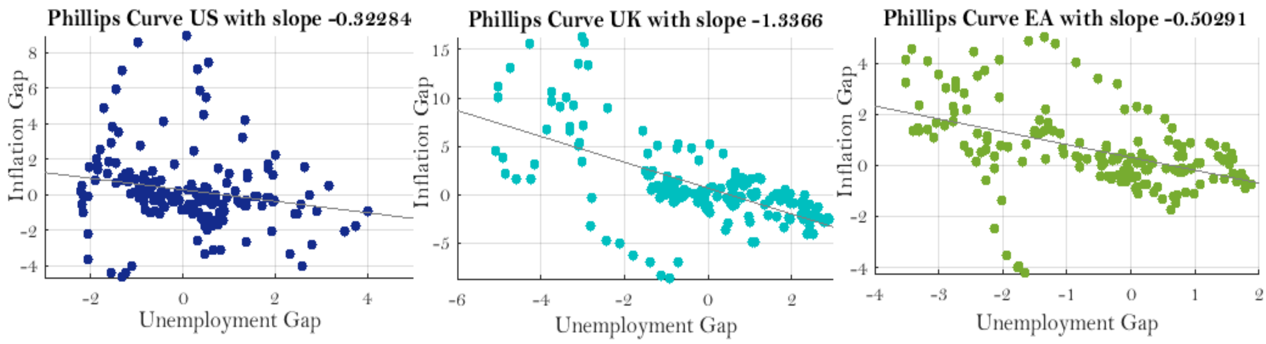


striking difference in terms of economic outcomes across countries is not in core inflation rates, but rather in natural unemployment rates, where the US and UK trends have converged around the year 2000, but the EA trend unemployment has remained considerably higher.

Using this measure of long-run trends, we can derive a measure of the relationship between unemployment and inflation assessing whether there is a constant (Phillips curve) relationship in the data and whether this relationship is different across economies. We think of this as a useful first step to understand whether there are substantial differences in the economic environment across the three economies (without taking a stand on the causes of potential differences). Note that we also do *not* take a stand on whether this is an exploitable relationship. Rather, we only present a reduced-form measure, studying how deviations of inflation from its trend are related to deviations of unemployment from its trend[6]. Figure 4 displays the estimated Phillips curve relationship in each economy. We find downward-sloping Phillips curves, but there is substantial heterogeneity in the estimated slopes. The absolute value of the slope is smallest in the US. Note that, given how we set up our Phillips curve regression, a smaller slope (in absolute value) means that any movement in inflation requires a larger movement in unemployment to stay on the curve. Interestingly, Phillips curve narratives are often featured in US monetary policy discussions.

[6]We use the posterior mean of τ_t as our measure of trend.

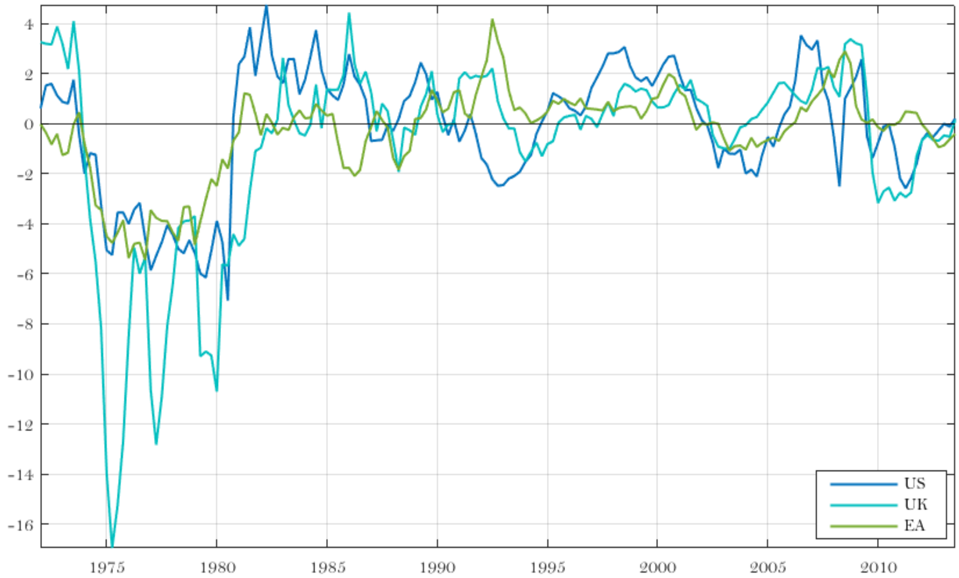
Figure 4: Phillips Curves across countries



Using our estimated long-run trends (or natural rates), we can ask how deviations (or 'gaps') from these trends evolve over time. In particular, we look at a measure of the real interest rate gap. In many models of monetary policy (and in particular the new Keynesian model), the real effects of monetary policy (due to sticky prices and sticky wages) appear because the central bank can influence the real rate of interest. In these models, the *long-run* or steady-state level of the real rate is outside of the central bank's control (and usually determined by technological progress). Our model naturally allows the implied long-run level of the real rate to vary over time. A natural measure of the monetary policy stance in our model is thus the deviation of the real rate (computed as the short-term nominal rate minus the rate of inflation) from its estimated long-run trend, which we plot in Figure 5. An advantage of this measure of the monetary policy stance is that we can compute it *without* having to identify a monetary policy rule or monetary policy shocks. To this end, the short-term interest rates need to be assumed as policy instruments of the central banks. We are not saying that this measure captures all aspects of monetary policy: during the Great Recession, for example, all three central banks in the economies in our sample used additional policy instruments such as quantitative easing and forward guidance. Nonetheless, by adopting this limited view of the monetary policy stance, we find policy differences across economies.

A first glance at Figure 5 reveals that the movements in our measure of the monetary policy stance are highly correlated across economies. The absolute levels (and the sign of the gap) can be substantially different across economies, though. The UK had a larger real rate gap in the 1970s, mainly driven by its higher inflation. Nonetheless, the timing of going to a negative gap and then back to a positive gap in the 1970s is broadly shared by all three of our economies (with the UK real rate gap lagging behind US and EA gaps). In the recent financial crisis, an interesting

Figure 5: Interest rate gaps



difference emerges: our estimates imply a tighter monetary policy in the EA for much longer during the Great Recession, which partly reflects the prolonged policy reactions to the European sovereign debt crisis.

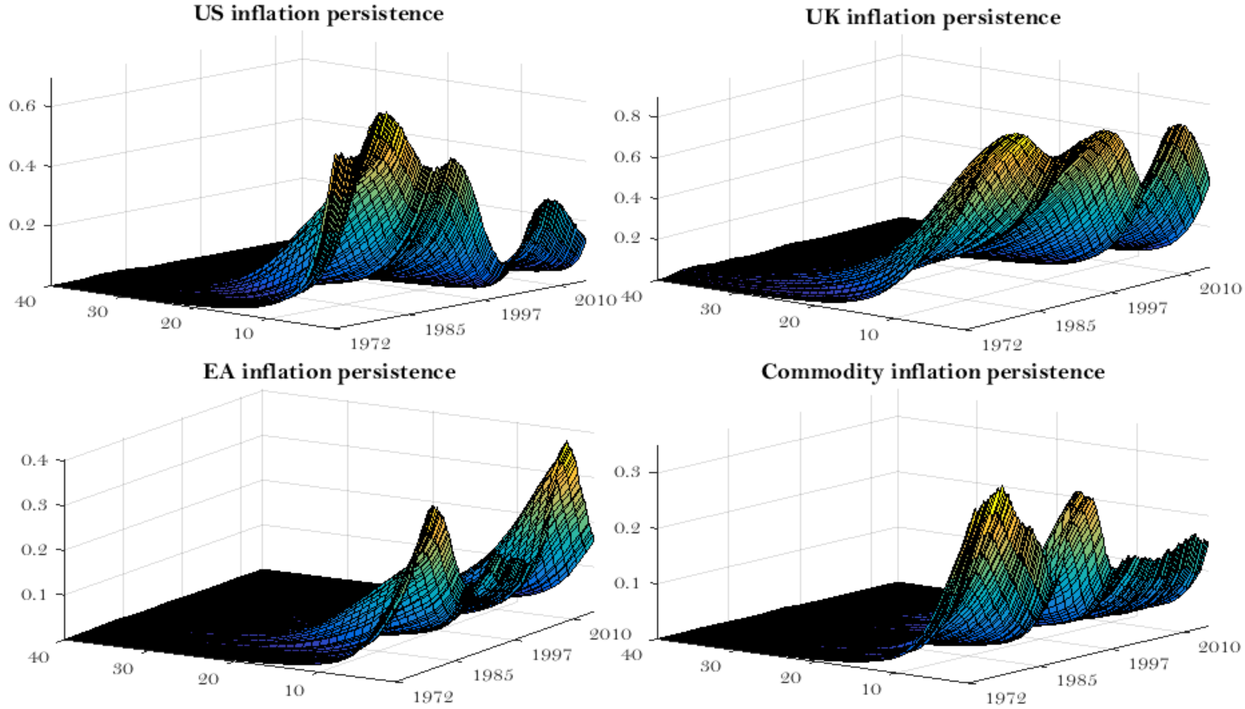
Next, we compute the measure for inflation persistence h steps ahead introduced by Cogley et al. (2010) and defined as

$$R^2_{t,h} = 1 - \frac{e_\pi \left[\sum_{j=0}^{h-1} A_t^j \Omega_t A_t^{j\prime}\right] e_\pi'}{e_\pi \left[\sum_{j=0}^{\infty} A_t^j \Omega_t A_t^{j\prime}\right] e_\pi'}, \tag{14}$$

where the vector e_π selects inflation from the vector z_t. The measure $R^2_{t,h}$ represents the proportion of total variation explained by past shocks (or equivalently, one minus the proportion of total variation due to future shocks). The measure takes values between zero and one, with values close to unity implying that past shocks die out slowly, making inflation more persistent and hence predictable.

Figure 6 presents the posterior mean of $R^2_{t,h}$ over time and horizon, computed using equation (14) for different draws of the parameters. One reason for a fall in inflation predictability is improvement in the ability of the central bank to handle inflation expectations through policy. Our results in Figure 6 for the US are similar to those presented in Cogley et al. (2010) and suggest that policy in the US started improving in the late 1970s and continued throughout the 1980s, making inflation harder to predict and analyze during this period. On the other hand, such policy advancements

Figure 6: Inflation persistence across countries



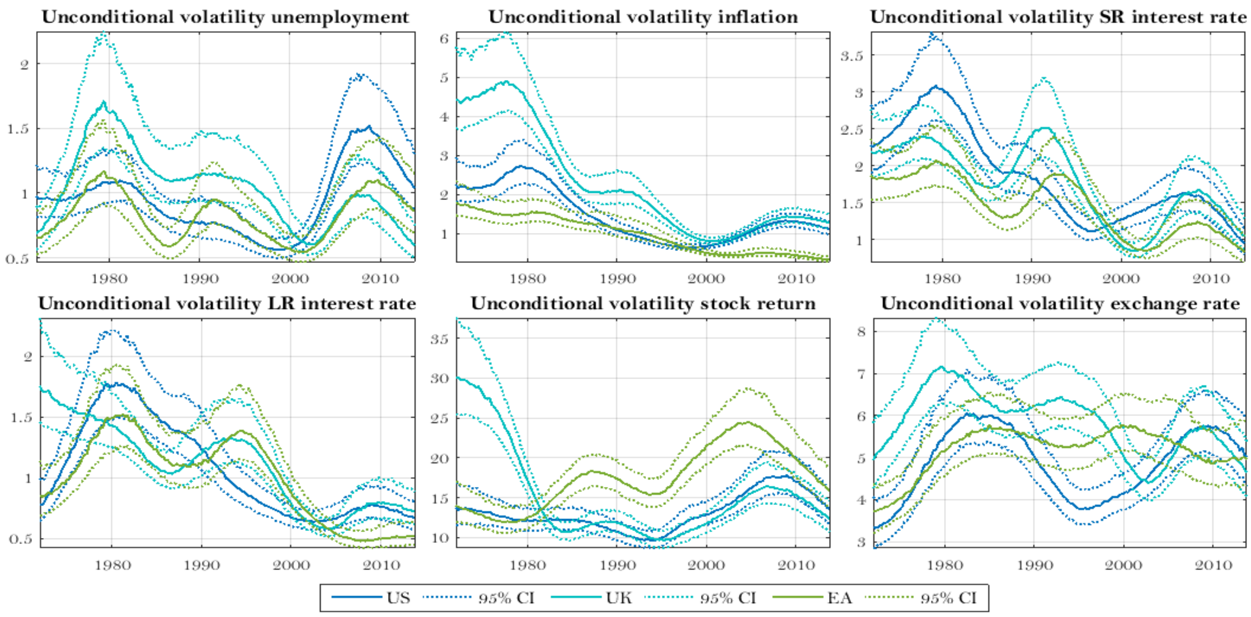
were already present in the EA earlier in the 1980s, and inflation persistence actually rose after the introduction of the euro in 1999. Finally, the UK inflation persistence is much higher throughout the sample relative to the US and EA, and the fall in UK persistence that we document occurs from 1990-2000, which is the period in which the Bank of England became an inflation-targeting central bank independent from the UK government.

We now turn to the volatility of the series. We compute the unconditional variance of the series at each point in time using the companion form in (11) and the VMA(∞) approximation in (12) as

$$U_t = \sum\nolimits_{j=0}^{\infty} A_t^j \Omega_t \left(A_t^j\right)'.$$

Figure 7 presents the unconditional volatility of the series in our model (given by the square roots of the first M diagonal elements of the matrix U_t) over time and across countries respectively. From the figure, the fall in volatility during the Great Moderation period can be seen in most series and is consistent with previous findings in the literature (e.g., Sims (1980), Bernanke and Mihov (1998), Kim and Nelson (1999), McConnell and Perez Quiros (2000), Sims and Zha (2006) and Primiceri (2005)). Interestingly, we find that the Great Moderation period starts later in the UK. If well-designed policy was the cause of the fall in the macroeconomic volatility in the US,

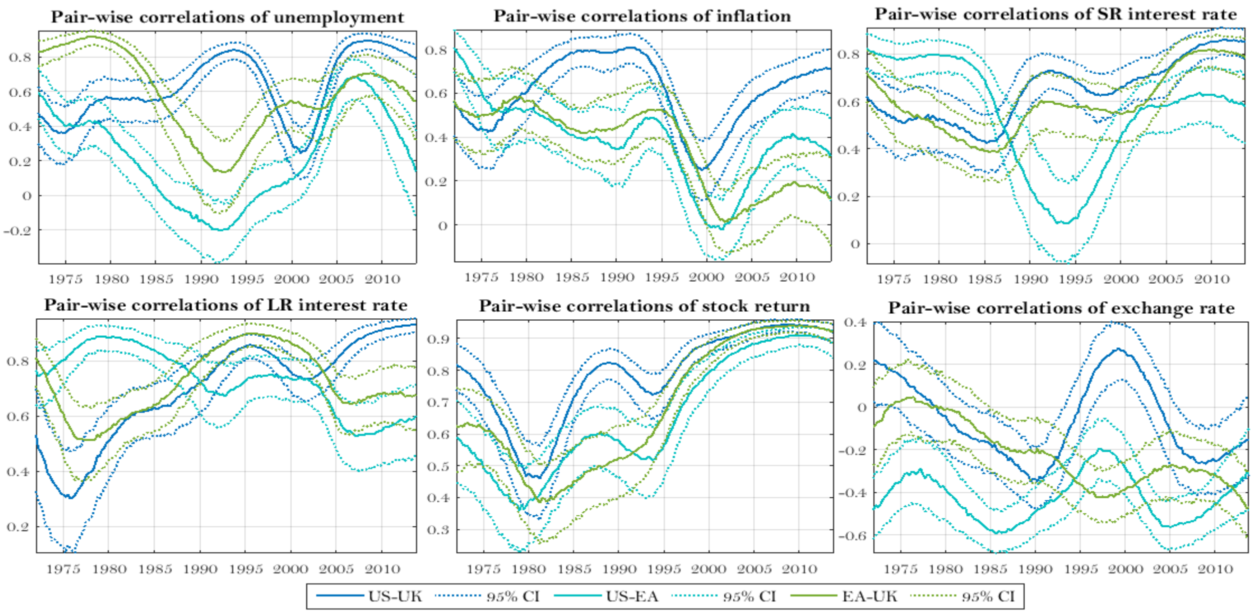
Figure 7: Unconditional Volatility



then one explanation for our result on volatility of British variables is that the UK underwent monetary policy improvements later. Particularly, the Bank of England adopted active inflation-targeting in 1992 and only became independent from the UK government in 1997. Unsurprisingly, we also discover an increase in the volatility of unemployment and stock market returns during the 2008 financial crisis. Similar trends are visible if we studied the conditional variances computed as $var\left(z_t|\mathcal{F}_{t-1}\right) = \Omega_t$. For the sake of brevity, we include these additional results in the supplementary Appendix.

One novelty of the reduced-form results presented in this section is the use of a joint multi-country estimation of the time-varying parameters of the VAR as well the application of the novel quasi-Bayesian approach, which delivers estimates for the drifting volatilities without the need to take a stand on the ordering of the variables in the system. This joint estimation approach also allows us to compute the evolution of the unconditional correlations of the series across pairs of countries, which we present in Figure 8. The main result in Figure 8 is that the correlation between US and UK variables is predominantly positive and stronger than any other pair (US-EU and UK-EU). One important finding is the strong negative correlation between USD and EUR effective exchange rates, weaker negative correlation between GBP and EUR rates, and the surprising periods of positive correlation between USD and GBP rates. These results are important

Figure 8: Pair-wise Correlations



for our structural shock analysis in Section 3.4, since the exchange rate channel is crucial for international monetary policy transmission. We also see most pair-wise correlations increasing during the 2008 financial crisis, implying an increased interdependence during this period. For example, the estimated correlations between the stock market returns across countries reach values close to unity after 2008. More evidence on the system-wide connectedness of our model as well as the implied networks across variables and countries can be found in Section 3.3 below.

3.3 Time-varying connectedness

In this section, we examine the interconnections between the variables/countries in our system and how they evolved over time using the framework of Diebold and Yilmaz (2014) and Demirer, Diebold, Liu and Yilmaz (2018). Our measure of connectedness is based on the variance decomposition of the VAR model and characterizes a weighted directed network. We adopt the generalized variance decomposition[7] of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) and make use of the VMA(∞) approximation of our TVP VAR model in (12). The variance decomposition

[7] If we had identified as many structural shocks as observables in our structural VAR analysis in Section 3.4, we could have constructed the variance decomposition according to our identified SVAR. Instead, in the next section we only identify three monetary policy shocks. The advantage of the results in this section is that they provide 'reduced-form' evidence that does not rely on our specific identifying assumptions.

is given by

$$G_{ij,t}(H) = \frac{\Omega_{t,ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_t^h \Omega_t e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_t^h \Omega_t \left(A_t^h\right)' e_i\right)}$$

where e_i is an $Mk \times 1$ selection vector with the i-th element unity and all the other elements zero. Roughly speaking, the (i, j)-th element of the variance decomposition matrix $G_{ij,t}(H)$ measures the fraction of variable i's future uncertainty due to shocks to variable j at H horizons in the future. Here, we choose the forecasting horizon H to be four quarters, so we consider one-year-ahead uncertainty.

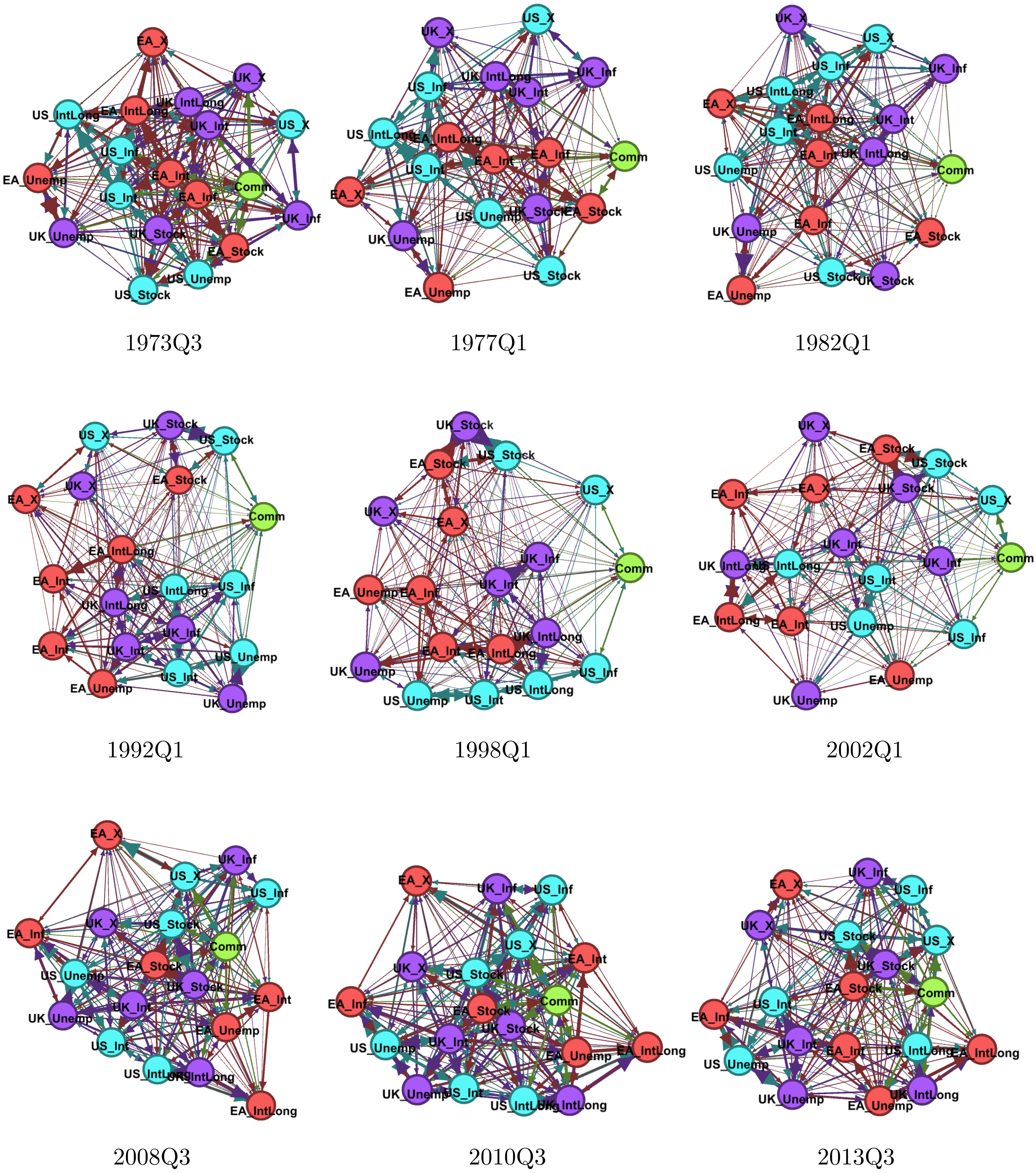
Following Diebold and Yilmaz (2014) and Demirer et al. (2018), we further normalize the variance decomposition matrix so that the row sum equals to one, $C_{i\leftarrow j,t}^H = \frac{G_{ij,t}(H)}{\sum_{j=1}^N G_{ij,t}(H)}$. After constructing the connectedness table, we visualize it via network "spring graphs". The color of each node represents which economy the variable is associated with: EA variables are red, UK variables are purple, US variables are blue, and the global commodity price inflation is green. Thickness of the edges of the graphs measures how strongly connected the two variables are, represented by the nodes at the ends of the edge. The strength of the edges is determined by the *average* pair-wise directional connectedness (i.e., $(C_{i\leftarrow j,t}^H + C_{j\leftarrow i,t}^H)/2$). The size of the arrows at the end of each node, on the other hand, measures the pair-wise *directional* connectedness 'to' and 'from' (i.e., either $C_{i\leftarrow j,t}^H$ or $C_{j\leftarrow i,t}^H$).

Figure 9 displays the network graphs for selected periods and reveals many interesting patterns across time. In general, we see a closer connection within each variable category. For example, the nodes for US, UK, and EA short-run interest rates are close to each other. This clustering feature reveals the synergy of economic environments and monetary policies across these three economies.

We find that during the first oil shock in 1973, commodity price inflation, which includes the oil price, plays a central role in the system and explains a large part of the variation in exchange rates and short-run interest rates across countries, as implied by the thicker green arrows. We also see that the effects on UK variables are larger in magnitude, which is consistent with the UK having experienced a much more severe oil crisis than the EA and the US. Similarly, we find an increased cross-variable and cross-country connectedness after the second oil shock of 1979, although commodity inflation does not play a central role anymore in 1982Q1, and instead we find that short- and long-run interest rates have become core in explaining variation across variables.

During the Great Moderation period (1992Q1 and 1998Q1), we document an interesting separation in the system between financial and macroeconomic variables, with stock market returns

Figure 9: Connectedness graphs for selected periods



Node name tags are abbreviated as follows. Unemployment: Unemp. Inflation: Inf. Short-run interest rate: Int. Long-run interest rate: IntLong. Stock return: Stock. Effective exchange rate: X. Commodity price inflation: Comm.

and exchange rates of our three economies forming a cluster, implying not much spillover effects between financial markets and the macroeconomy. During these periods, we find that UK short- and long-run interest rates are strongly connected to UK inflation with large portions of the variation in inflation explained by the rates and vice versa, a possible consequence of the introduction of inflation targeting and its formal independence from the government in 1992 and 1997, respectively. In 2002Q1, after the short 2001 NBER recession, we continue to find some separation between financial and macro variables, although less clear than in the previous periods.

During the 2008 crisis and the periods afterward, we uncover an increased global interdependence (implied by the thicker arrows) and importantly, we find that stock returns are now central in the estimated network, implying large contagion from financial markets to the macroeconomy. Particularly, stock returns are directly explaining large proportions of the variation in unemployment, inflation, and interest rates across countries. Our results are very similar in 2010Q3, with commodity price inflation now also playing a central role in the system.

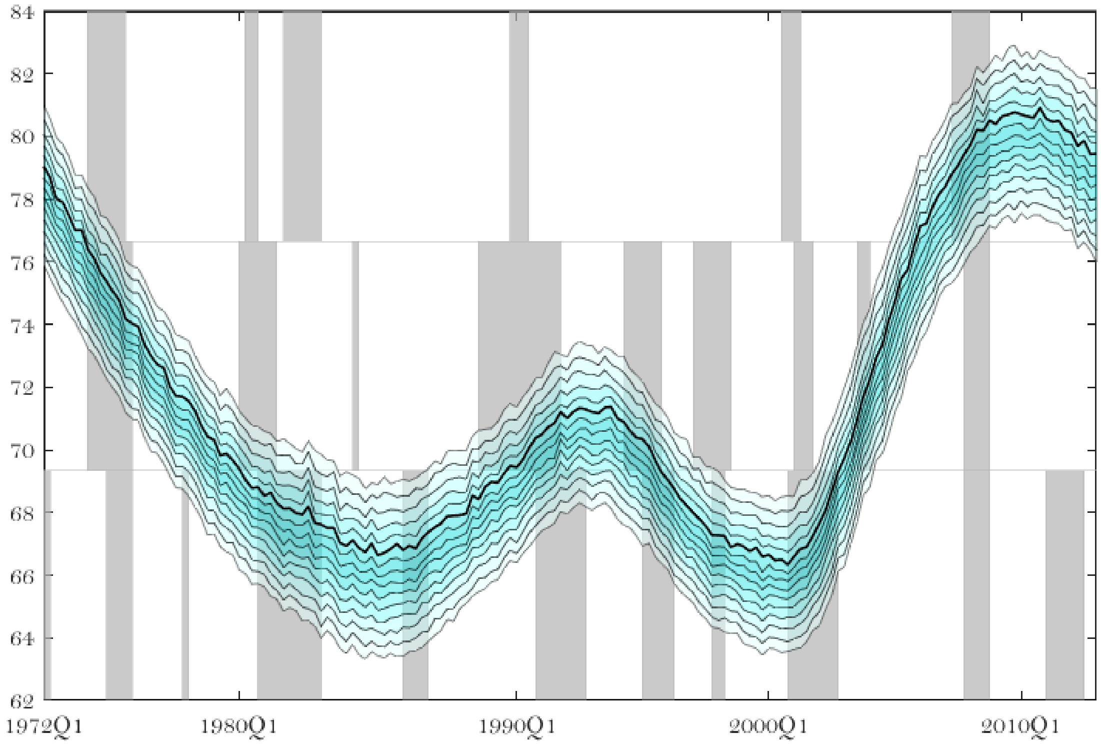
The graphs presented so far try to uncover relationships between different variables in our model. We can also use the information in those graphs to get a sense of how important unexpected movements in other variables are on average in our system over time. This gives us an estimate of how important interdependence or the 'network structure' is in our data and, in particular, how it has evolved over time. To achieve this goal, we measure the interaction across variables net of the self effect by averaging over the connectedness table excluding the diagonal elements,

$$C_t^H = \frac{1}{N} \sum\nolimits_{i,j=1, i \neq j}^{N} C_{i \leftarrow j,t}^H.$$

Figure 10 presents the posterior median and the 64% estimated posterior sets of our system-wide connectedness measure, evolving over time, and the shaded grey top, middle, and bottom areas display recession dates in the US, UK, and EA, respectively[8]. In general, Figure 10 suggests that periods characterized by economic downturns (such as the Great Inflation in the early 1970s, the EA and UK recessions around the middle 1990s, as well as the financial crisis, the Great Recession, and the European sovereign debt crisis in the late 2000s) are associated with higher overall connectedness. Particularly, over 80% of the variance of our model is explained by past shocks to other variables during the recent crisis, compared to 60% in the Great Moderation. This result suggests that during economic distress, correlations and interdependencies between variables

[8] For the US, we use NBER recession dates; for the UK and EA, we use an OECD monthly recession indicators from peak through trough and define a recession in the UK and EA as five consecutive months of decline in each, respectively.

Figure 10: System-wise connectedness



and across countries increase, which is consistent with findings in the financial GARCH literature (e.g., Engle, Ledoit and Wolf (2017)) as well as macroeconomic and financial network literature (e.g., Demirer et al. (2018)). Nevertheless, this finding cannot be interpreted causally - these stronger network effects could also be a consequence of the effects of the Great Recession.

3.4 Structural analysis

In this section, we turn to the very questions we asked at the beginning of this paper, namely how monetary policy and its associated domestic and international effects differ across economies and over time. To address the further question of policy coordination, we focus on the behavior of foreign nominal interest rates to unexpected changes in the three policy shocks. This is a simplifying assumption we impose in our analysis, which might be unrealistic in practice, since we would expect that central banks also react to the systematic fraction of monetary policy of other major banks rather than only to unanticipated shocks. However, if this were indeed the case, the results presented in this section would only underestimate the true level of policy cooperation.

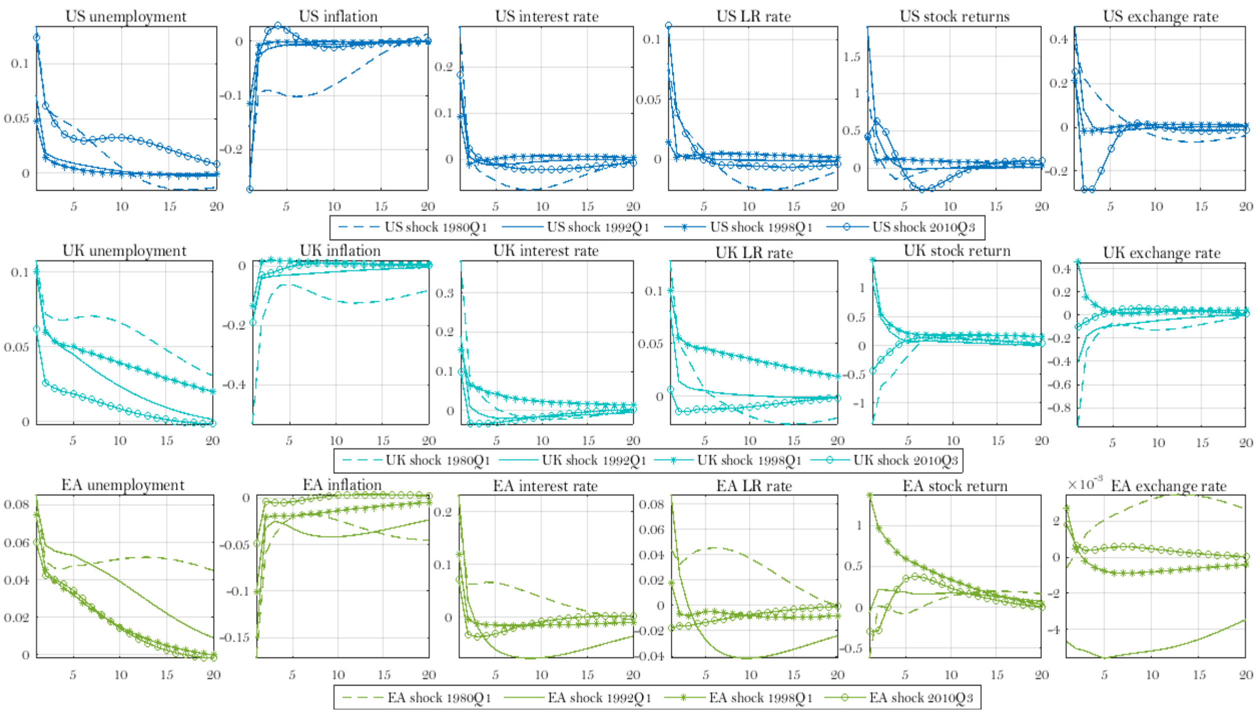
Our identifying strategy for the economy-specific monetary policy shocks employs sign and magnitude restrictions of the impulse responses, along the lines of Uhlig (2005), Canova and Nicolo (2002), and Faust (1998). Specifically, we impose the sign restrictions that in response to a monetary policy shock in country i, the short-term nominal rate in that country increases, the inflation rate decreases, and the unemployment rate increases. Moreover, to distinguish monetary policy shocks across countries, we also impose that a monetary policy shock in country i must have the largest effect in magnitude on inflation, unemployment, and interest rate in country i. These magnitude restrictions can be powerful tools that help shrink the identified set of impulse responses, as carefully detailed in Amir-Ahmadi and Drautzburg (2017).

More formally, we use the VMA(∞) approximation of the companion model in (12) and let P_t denote the Cholesky factor of Γ_t^{-1}. To impose our identifying restrictions, for each period t, we first draw from a family of orthogonal matrices $Q \in \mathcal{Q}$ of size M, and the resulting impulse responses at every point in time, given by $\iota_{th} = [A_t^j]_{1:M,1:M} P_t Q'$, span the space of all possible responses[9]. Next, we employ rejection sampling, only retaining draws of ι_{th} that satisfy all sign and magnitude restrictions. Namely, we check if a shock can be found for each economy $i \in \{1, 2, 3\}$ satisfying the following: an increase in domestic interest rate ($r_{t0}^i > 0$) reduces on impact (i.e., $h = 0$) domestic inflation ($\pi_{t0}^i \leq 0$), increases domestic unemployment ($u_{t0}^i \geq 0$), and, in addition, the shock has the highest magnitude effect on the three domestic variables: $\left|\Delta r_{t0}^i\right| > \left|\Delta r_{t0}^j\right|$, $\left|\Delta \pi_{t0}^i\right| > \left|\Delta \pi_{t0}^j\right|$ and $\left|\Delta u_{t0}^i\right| > \left|\Delta u_{t0}^j\right|$ for all $j \neq i$. To implement the calculation of the impulse responses conditional on reduced-form estimates, we use the algorithm outlined in Rubio-Ramirez, Waggoner and Zha (2010), which allows us to efficiently explore the space of candidate impulse responses. Notice that we leave unrestricted the direction in which a policy shock in a given country might affect the remaining domestic variables (long-run interest rates, exchange rates, and stock returns) as well as all foreign variables. As a consequence, the results on the size and direction of the spillover effects of shocks across countries are informed by the data only and not imposed as a maintained assumption. In the main text, we focus on the point-wise impulse responses (computed as the posterior mean) to a one standard deviation shock for selected time periods. The supplementary Appendix contains both the associated posterior error bands as well as 3D plots that display the entire evolution of the posterior mean responses. For the sake of clarity, throughout this section and the Appendix, we always use dark blue for the US policy shocks, lighter blue for UK shocks, and green for EA shocks.

In Figure 11, we show the responses of all domestic variables to a monetary policy shock in

[9]Note that we draw different Qs for different periods. $[\cdot]_{1:M,1:M}$ selects the first $M \times M$ block of a given matrix.

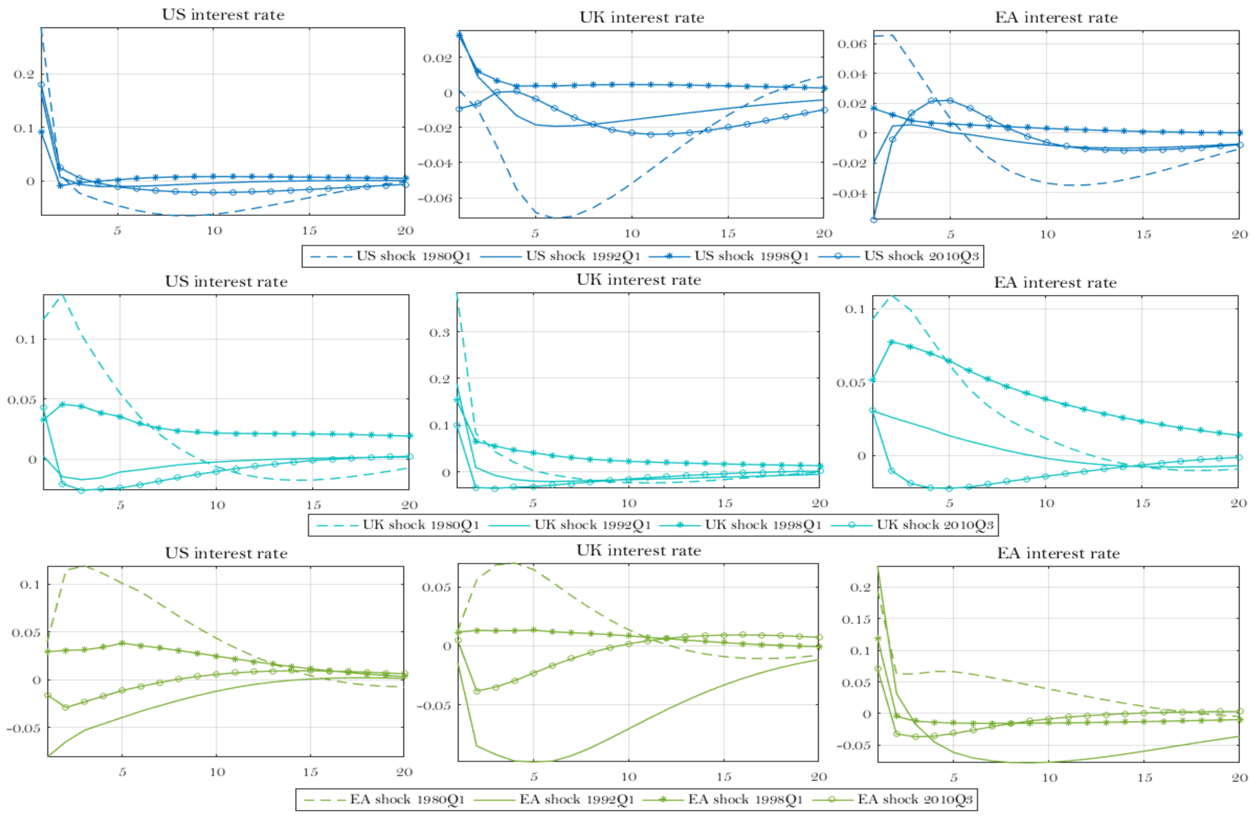
Figure 11: Domestic effects



that economy. First, the responses of the nominal interest rate in all economies are relatively short-lived and less persistent than, for example, the corresponding unemployment response. The persistence of the interest rate responses is in line with the literature (Christiano et al., 1999). The main difference in the associated unemployment and inflation responses across time seems to be in terms of persistence and magnitude - monetary policy shocks are much longer-lived in the 1980s and 1990s than in the subsequent periods. Moreover, EA monetary policy has smaller effects on impact on EA inflation and unemployment, even though the impact on nominal interest rates across countries is of a similar magnitude. In general, we find a decreased responsiveness of inflation and unemployment over time for all economies, particularly during the Great Moderation. This fall in domestic responsiveness to monetary policy shocks after the 1980s is consistent with findings in Boivin and Giannoni (2006), who attribute it to policymakers becoming more efficient in managing agents' expectations.

In terms of stock return responses, the US is special in that for all selected time periods an unexpected increase in the policy instrument increases the stock market index, while for the UK and EA, we find that in periods characterized by financial distress and monetary stimulus (1980 and 2010) the responses are negative, suggesting asymmetry in the responses of financial markets to policy shocks. Finally, exchange rates mostly move in the expected direction: monetary tightening causes an appreciation in the effective exchange rate. One exception is the UK, as well as the EA in periods before the introduction of the euro. This is expected, as the UK and the aggregated individual European states prior to 1999 resemble more closely small open economies that have less control over the value of their currencies in international markets.

Figure 12: Interest rate spillover effects

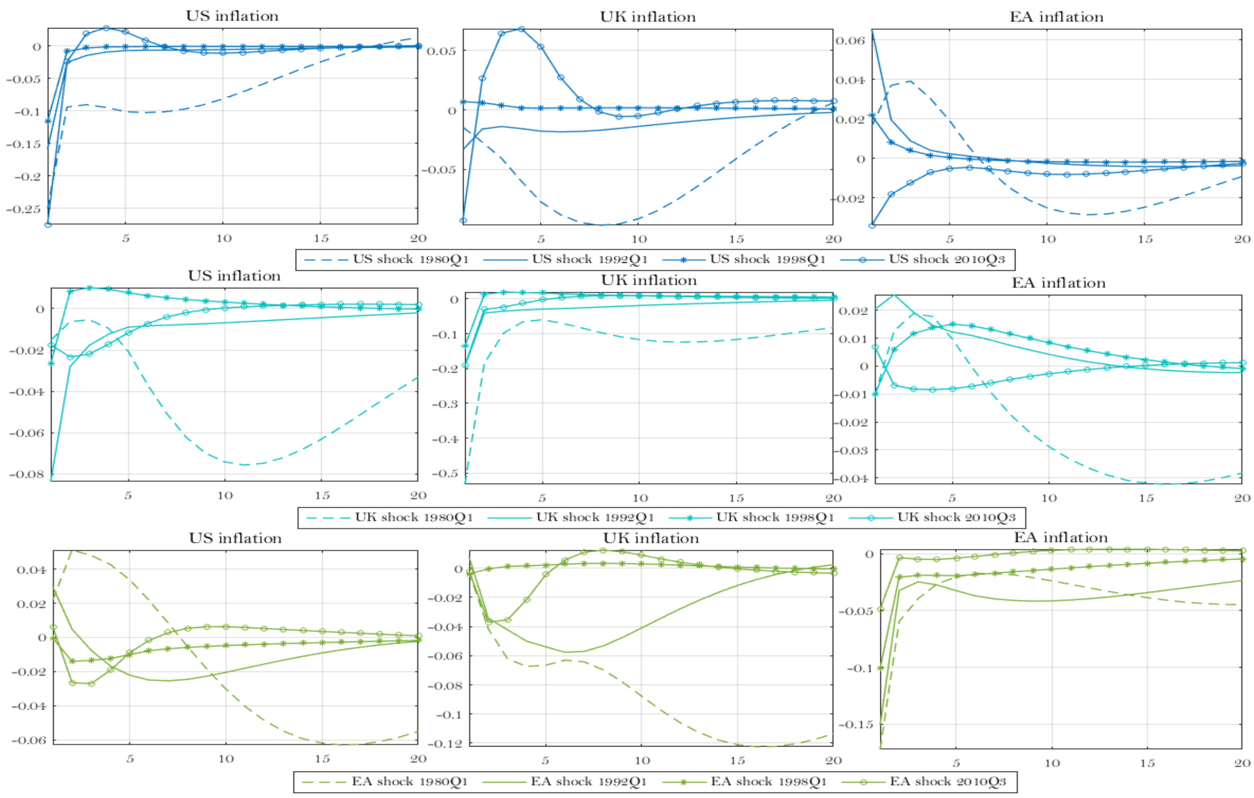


Next, we turn to cross-country spillover effects[10]. Figures 12-14 present the responses to monetary policy shocks of interest rates, inflation, and unemployment rates, respectively, in each economy (first row US shocks, second row UK shocks, and third row EA shocks) for various time periods (we thus repeat the domestic effects in the diagonal of Figures 12-14 to ease comparison). Figure 12 helps us address the question of monetary policy coordination. Particularly, we find evidence

[10] One caveat to the presentation of our results is that we relegate posterior bands to the Appendix. Given that our error bands feature both estimation and identification uncertainty, some of the error bands contain zero. Nonetheless, we find it useful to characterize our model's 'best guess' (or point estimate) of what the spillovers are.

of policy coordination only during the 1970s and early 1980s, and zero or negative cooperation afterwards. To put this result into historical context, the 1970s and 1980s were periods when

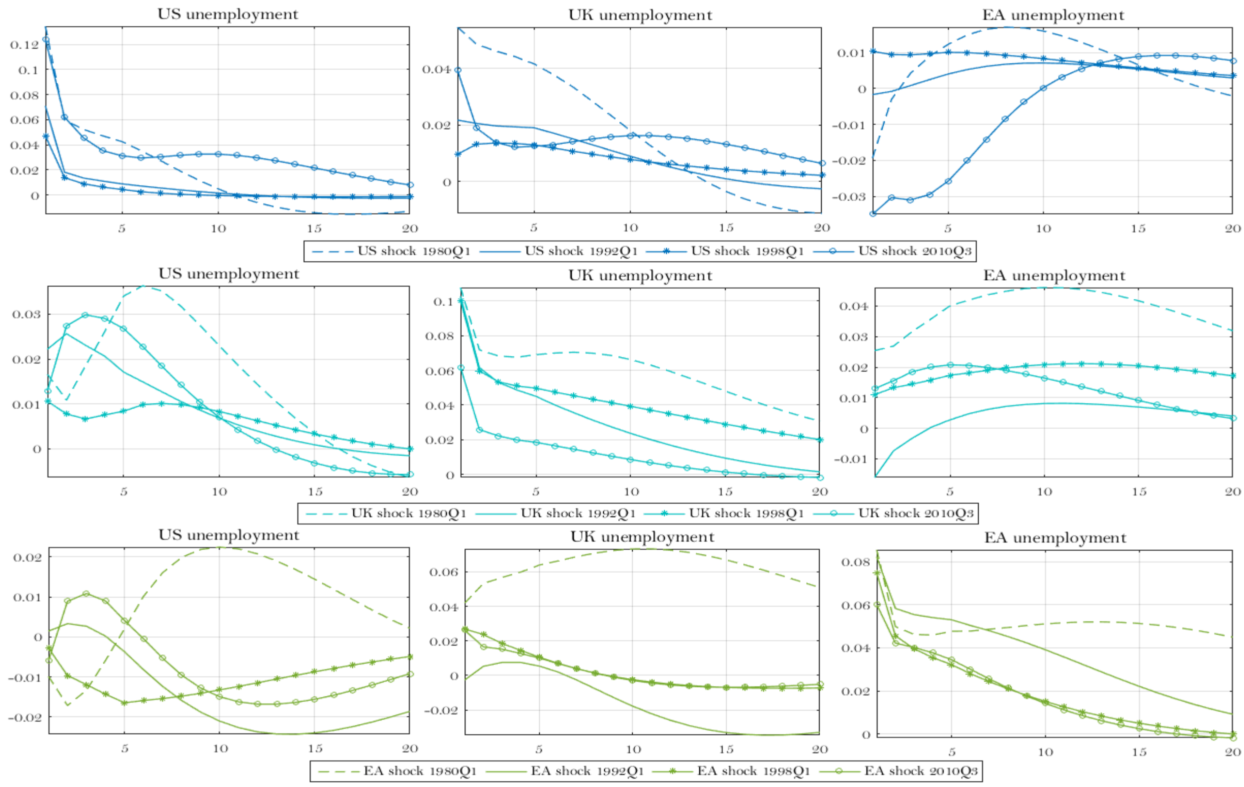
Figure 13: Inflation spillover effects



central banks across the world faced large exogenous oil shocks, which suggests the possibility of policy cooperation as an optimal response, rather than a zero-sum game, in the face of these large exogenous shocks.

The international effects of policy shocks on inflation and unemployment display the same sign spillover effects as the corresponding domestic effects for most shocks in the early 1980s. Particularly, we find that during this period, these favorable spillover effects are larger, more persistent, and often statistically significant, which could be a consequence of the documented evidence of cooperation that we find between central banks in this period. After 1980, we find either negative 'beggar-thy-neighbour' or insignificantly different from zero spillover effects across economies.

Figure 14: Unemployment spillover effects



4 Conclusion

To answer the questions we posed in the beginning of this paper on how monetary policy spills across borders and whether it evolves over time, we adopt a novel quasi-Bayesian semi-parametric approach to estimate the parameter time-variation in a medium-sized VAR model. We first employ our estimated model to compute various reduced-form quantities in order to understand important differences across countries in the long-run moments of the series implied by our model. We combine this novel estimation methodology with recent advances in the literature linking VARs and network analysis, in order to estimate the time-varying network structure of our model. An additional contribution of our paper is the design of an identification strategy that allows us to jointly identify country-specific policy shocks through a combination of sign and magnitude restrictions, providing some useful insights on the international transmission of monetary policy.

From our empirical results, several conclusions emerge. First, we find that the US and the UK share more similarities than the EA, which is natural since the ECB faces a considerably different environment as the policymaker of a currency union comprised of diverse member states. This is particularly evident in our measure of the monetary policy stance as well as in the domestic responses to monetary policy shocks. Our reduced-form analysis also points to some meaningful changes in the UK monetary policy after the Bank of England underwent structural changes in the 1990s. Second, we uncover an increased connectedness between the variables in our model during the recent financial crisis, and more generally, in periods with financial distress. While we find this result compelling, we are cautious to conjecture on whether increased connectedness is the cause or merely a symptom of recessions. Finally, our structural shock analysis suggests that monetary policy shocks were larger in magnitude and more persistent in all countries in the early 1980s than in any subsequent periods. In the same period, we also find evidence for positive spillover effects of policy between countries as well as policy coordination between the three central banks analyzed.

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