Quantifying spillovers among regions[#]

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Abstract

The standard procedure for quantifying spillover effects of changes in economic fundamentals among separate regions (or countries) is to link the regions through predetermined weights – for example through fixed weighted trade indices or fixed spatial weights based on geographical distance. We provide a method for quantifying spillover effects among the U.S., the euro area, and the U.K. using spatial weights that are determined endogenously. We specify a new spatially augmented VAR model and we introduce a Bayesian estimation technique to freely estimate and quantify spatial interactions. We are able to quantify the effects of shocks to economic fundamentals in the three regions considered without imposing *a priori* restrictions on the size and directions of the spillovers. To illustrate our technique, we quantify the spillover effects of a series of shocks, including the recent rises in inflation and money supply shocks, in each of the three regions under consideration on the other regions.

Keywords: Spillovers inflation transmission; Spatial

1. Introduction

Recent studies on spillovers among regional economies have focused on the use of spatial estimation and network analysis.[1] A common feature of this work is that it assumes the existence of a known underlying structure for the network or the spatial relationships under investigation. In this connection, studies using spatial estimation have imposed a fixed and predetermined weighting matrix because it has not been possible to estimate a large system without imposing this restriction. A problem with this procedure is that the fixed weighting matrix effectively determines the amount of spillovers *a priori*.

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[1] Spatial estimation and network analysis are both concerned with understanding spillovers. Recent studies that examine the effects of spillovers using these methods include Gibson et al. (2017), Elhost et al. (2018), Cerdeiro and Komaromi (2020), and Gibson et al. (2022).

Another approach to estimating spatial effects was developed by Hall et al. (2023). Those authors initially estimated the determinants of inflation in three regions – the United States, the euro area, and the United Kingdom – using VARs comprised of seven domestic variables – including, money supply growth, fiscal positions, oil price, and supply-side constraints – for each region.[2] To examine spillover effects of inflation in the other two regions on the third region, the authors added the inflation variable in one region in the VARs in the other two regions, which is an approach that the authors considered to be "in the spirit" of a spatial model (Hall et al., 2023). This approach increased the size of the VAR structure from seven equations to nine equations for each of the three regions.

In this paper, we investigate the spillover effects of shocks among the three regions – the United States, the euro area, and the United Kingdom. We contribute to the literature in two main ways. First, while the typical approach used in the literature on spillovers has, as mentioned, been to impose a fixed weighting matrix, we develop a new Bayesian technique for unrestricted spatial estimation that allows us to freely estimate the spatial weighting matrix from which we derive spillover effects among the regions. We then apply this technique to quantify the spillovers among the three regions in a full spatial setting with an endogenously estimated spatial weighting matrix. Second, we implement this procedure using a new model which we call a spatially augmented VAR. Specifically, whereas previous work on VARs has treated regions in isolation of each other, in this paper we allow a full set of spatial spillovers. By doing so, we are able to estimate spillover effects that are not dependent on preassigned weights.

The remainder of this paper consists of five sections and two appendices. Section 2 provides a literature review. Section 3 describes what we term a spatially-augmented VAR. This is a VAR for a number of regions (in our case 3) which is augmented by contemporaneous spatial effects from the other regions in the system. Section 4 presents a new Bayesian technique that allows the estimation of large spatial models without imposing a fixed pre-determined weighting matrix. Section 5 presents the spillover estimates derived by applying this technique. Briefly to anticipate, the results provide evidence showing that shocks to the U.S. have a much stronger influence on the euro area and the U.K. than the reverse. Shocks to the euro area are found to spillover into the U.K., and with a somewhat smaller effect, to the U.S., while shocks to the U.K. only have a very small spillover into the other two regions. Section 6 concludes. Appendix A provides the definitions of variables while Appendix B describes the derivation of the shocks used to estimate spillover effects.

2. Literature review

Simple VAR models with inflation rates have been recently used to study inflation spillovers among countries and/or regions. Istiak et al. (2021) investigated inflation spillovers among the G7 countries using monthly data from 1956 M6 to 2020 M12. Those authors built a simple stationary VAR model with inflation rates in the G7 countries, and then quantified the spillover effects using either the forecast error variance decomposition provided in Diebold and Yilmaz (2012) or the frequency response function provided in Baruník and Křehlík (2018). Their

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[2] The VARs with seven variables were derived from larger VARs following a general-to-specific methodology.

findings suggest the U.S. and Japan are the main transmitters of inflation in the G7 group. Using the same variance decomposition technique, Al-Nassar and Albahouth (2023) estimated a simple VAR model using inflation rates of G20 countries to quantify the inflation spillovers among those countries. The estimation period was 1992 M1 to 2022 M3. Their results show that the U.S., Canada, and Italy are net transmitters of inflation, while France, Germany, Japan, and the U.K. are net receivers. However, neither of the two studies discussed above control for the factors that could affect inflation in the VAR models.

Apart from focusing exclusively on inflation, several studies included additional macro variables in the VAR models to investigate the inflation spillovers. Elsayed, Hammoudeh, and Sousa (Elsayed et al., 2021) used a simple VAR model with inflation rates and a multivariate ARMA(1,1)-DECO-GARCH(1,1) model to evaluate the spillovers between oil price inflation and CPI inflation in the G7 countries and China from 1987 M6 to 2020 M6. They found that oil price inflation was a crucial transmitter of spillovers to CPI inflation, especially for the U.S. Ciccarelli and García (2021) used a simple VAR model with three inflation rates (global inflation, U.S. inflation, euro area inflation) and four inflation expectation measures (the short- and long-term inflation compensation in the U.S. and the euro area, respectively) to study the effects of a rise in the U.S. inflation rate in 2021. Their findings suggest that a rise in U.S. inflation contributed to that in the euro area. Azad and Serletis (2022) used a multivariate GARCH-in-Mean VAR and a structural VAR model to study the spillovers of U.S. monetary policy to seven inflation targeting emerging economies. In the former model, U.S. monetary policy uncertainty was measured as the conditional volatility of U.S. policy rates. In the latter model the authors used a monetary policy uncertainty index for the U.S. The spillover effects were examined by simply adding policy uncertainty measures into each of the regional VAR models. The findings suggested that higher U.S. monetary policy uncertainty had an impact on inflation and emerging economies.

Spillover effects have also been identified in sovereign spreads and banking systems in the euro area countries. Gibson et al. (2017) used a three-equation simultaneous-equation model to account for the spillover of sovereign spreads, sovereign ratings and bank ratings in the five southern European countries. After controlling for economic and political fundamentals, the authors found that spreads and ratings among those countries were strongly interrelated during the euro area crisis. Subsequently, Gibson et al. (2022) applied a simultaneous equation spatial autoregressive (SESAR) model with a pre-determined weighting matrix to examine the spillover effects between the sovereign spreads and banks' share prices among ten euro area countries (five northern and five southern countries). The authors found strong evidence of spillover effects during the euro area crisis. While the spillover effects were found to be weaker in the southern countries, the authors also found that spillover effects helped stabilise banking systems under small shocks in the northern countries.

Elhost et al. (2018) reviewed and compared the spatial and global VAR models in the literature on spillover effects. They discussed the importance and implications of the weighting matrix and distinguished two types of models incorporating several features, including the way to determine the weighting matrix. Spatial VAR models often used an exogenous location-based, time-invariant matrix, while global VAR models typically used macro-financial-data-based matrices that could be time variant and different for each variable. Neither of the two types of models needed to be estimated endogenously. In contrast, in this study we make the weighting matrix endogenous and we estimate the matrix from the data. Elhost et al. (2018) found spillover effects between GDP and bank credit growth rates in European countries during

2001Q1 to 2015Q4, conditional on four pre-determined weighting matrices using macro and financial data in a global VAR model.

Spillover effects have also been examined in other contexts. For example, Cerdeiro and Komaromi (2020) used a fixed effect model to examine the causal effect of the spillovers from one country's lockdown to other countries' import growth, using seaborne trade data of cargo ships. They defined a lockdown exposure measure with the fraction of pre-Covid import shares, the stringency of lockdown measures, and the shipping time of sea cargos. The authors found that lockdowns and supply disruptions played a significant role in the collapse of trade, although these effects were short-lived. Using fixed effect models, Das et al. (2021) studied the effect on the sectoral activity of a shock within its own sector and shocks from other sectors in a large sample of countries from 1995 to 2014. Based on the historical estimates, they found that such sectoral spillover effects were sizeable, comprising a significant fraction of the overall decline in activity during the Covid-19 pandemic.

Since the initial work of Cliff and Ord (1973) the literature on spatial models has grown enormously.[3] It is not possible to fully survey this literature here but we will discuss some of the key elements of it in the next section. A common feature of most of these papers is that underlying their analyses is a set of predetermined weights that govern the form of the spillovers. These predetermined weights specify the form of the spillovers and so, to a large extent, the issue investigated is fixed 'a priori'. In this paper, we provide a model (the spatially augmented VAR) where these spillovers are estimated endogenously based on a Bayesian technique for the estimation. We then apply this technique to investigate spillovers among the U.S., the euro area and the U.K.

3. The spatial model and the VAR

Cliff and Ord, 1973, Cliff and Ord, 1981) introduced the spatial autoregressive (SAR) model. In their original approach, a number of cross sections are allowed to have explicit contemporaneous spillovers which are governed by a known spatial weighting matrix. This basic modelling approach has been developed to allow for systems of spatial autoregressive equations (SESAR) following the work of Kelejian and Prucha, 2004, Baltagi and Pirotte, 2011, Yang and Lee, 2017, and Liu and Saraiva (2019). This model allows for a system of equations containing m cross sections (regions, countries, firms, etc.) which are observed across t periods and which are spatially interrelated. When referring to a spatial lag effect it is important to emphasise that these effects are contemporaneous effects and the SESAR model does not refer to dynamic lags as the term is used in time series econometrics, although the SESAR can be extended to have time lags. The general SESAR model may be stated as;

$$Y_{nm,t} = W_n Y_{nm,t} \Psi_{mm} + X_{nk,t} \prod_{km} + v_{nm,t} \tag{1}$$

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[3] See for example, Siano et al. (2020) or Anselin et al. (2004) and a good survey of this literature may be found in Mendes and Mendes (2015).

where $Y_{nm,t}$ an *n* by *m* matrix consisting of *m* endogenous variables in each region over *n* regions all indexed by $t = 1 \ldots T$. W_n is an *n* by *n* matrix that summarizes the spatial interactions and is often called the spatial weighting matrix: it is often row normalized with zeros on the diagonal. is an *m* by *m* matrix of parameters for the spatial effects. $X_{nk,t}$ is an n by *k* matrix of *k* exogenous variables. is a *k* by *m* matrix of parameters on the exogenous variables. Finally, $v_{nm,t}$ is a matrix of *n by m* errors which are assumed IID with zero mean and covariance matrix Σ_{nm} for $t = 1 \ldots T$.

The key matrix that makes this model operational is the spatial weighting matrix W_n. This matrix is a known matrix and can potentially be very large. Note that the same W_n is imposed on all variables in each region. In the literature, this is often derived from geographical data, such as the distance between capital cities or a common border (contiguity).

In order to investigate the spillovers in inflation between the U.S., the euro area, and the U.K., Hall et al. (2023) discussed the possibility of using a SESAR model but were unable to implement this technique because of the restriction imposed by the weighting matrix. Namely, in equation (1) the W_n matrix essentially determines the relative size of the spillover between the regions; what is estimated is the absolute size of the total spillovers. The question those authors addressed was: what is the relative size of the spillovers? This issue cannot be addressed in a standard spatial model because the spatial weighting matrix is determined *a priori*. They therefore estimated a regionally augmented VAR for the three regions of the following form:

$$Y_{it} = B_i + A_i(L)Y_{i,t-1} + C_i(L)Y^*_{i,t-1} + u_{it} \tag{2}$$

where i represents the three regions, $i = 1 \ldots 3$, Y_{it} is a vector of variables relevant to inflation in each region including inflation itself, B_i is a vector of constants, $A_i(L)$ and $C_i(L)$ are matrix of lag polynomials, $Y^*_{i,t-1}$ is inflation in the other two regions and is a vector of error terms. This set-up is essentially nothing more than a standard VAR augmented with terms from the other two regions. We could put this into the form of a spatial model by augmenting (2) with a set of spatial terms.

$$Y_{it} = B_i + A_i(L)Y_{i,t-1} + \Psi W Y_t + u_{it} \tag{3}$$

where Y_t stacks the Y_{it} vectors into a single vector and W and Ψ are a suitably dimensioned spatial weighting matrix and set of parameters, respectively. We can think of this as a spatially augmented VAR. This model nevertheless is subject to the same problem as (1) in that, if we want to estimate the relative size of spillovers of inflation, this is impossible because the spillovers are governed by the pre-determined W matrix. We can further generalise (3) to relax this restriction by using an estimated matrix in place of W and Ψ. Thus;

$$Y_{it} = B_i + A_i(L)Y_{i,t-1} + DY_t + u_{it} \tag{4}$$

where D is a suitable dimensioned, freely-estimated matrix of parameters that capture the full spillovers among the variables in Y_t, with suitable zero restriction such that the elements of Y_t, which are the same as those Y_{it}, have zero elements in D and $u_{it} \perp u_{jt}$ for $i \neq j$.

The problem with this model, however, is that D is potentially a very large matrix so that in many contexts standard estimation techniques will be unable to estimate this matrix because the number of parameters can easily be larger than the number of data points. Hence, the usual procedure is to restrict it with a fixed spatial weighting matrix.

To deal with this problem of estimation, in what follows we introduce a Bayesian estimation technique which allows the possibility of estimating a larger number of parameters than data points.

4. Endogenising the spatial weighting matrix

The details of our proposed Bayesian estimation technique are available from the authors. Here, we provide an intuitive account of the estimation technique in how that technique surmounts the problem which arises in a standard estimation procedure. We then present a brief discussion of Bayesian shrinkage priors and Variational Bayesian (VB) methods.

There are essentially two problems in estimating equation (4). First, we have to deal with the problem of endogeneity in the contemporaneous variables Y_t in equation (4). Second, the matrix D can have a potentially very large dimension that can easily exhaust the number of observations available. The first issue has been extensively discussed in the spatial literature. A range of instrumental variable techniques and a Maximum Likelihood estimation have been used. The remaining problem concerns the dimension of the D matrix. Typically, in any classical econometric technique, as the number of parameters to be estimated reaches the number of data observations available, the estimator will achieve a perfect fit. Whatever criterion is used for minimisation (least squares, an IV minimand or the negative log likelihood), it will achieve its optimal value and estimation becomes impossible. In many spatial applications the number of elements in the D matrix may far outweigh the number of observations. Hence, the traditional procedure is to fix the W matrix in equation (3) 'a priori', based on, for example, geographical distance. This approach, however, defeats our objective here because it is precisely the elements of the D matrix that we are interested in investigating. Central to the Bayesian approach is a set of priors that essentially pulls the less important parameter estimates toward zero.

Unlike the classical approach, where the parameters are assumed to be unknown but fixed, Bayesian methods view the parameters as random variables coming from relevant posterior distributions. In our case, we can perceive the posterior distribution of the parameters consisting of two distinct parts. The first part involving the data information, is akin to the standard likelihood function and would reach its optimum when the model has a perfect fit. The second part involving the priors is a distribution penalizing the parameters that are close to zero but not exactly equal to zero. Intuitively we are allowing the more important parameters to stay where they are while shrinking the less important parameters to zeros.

There are a range of popular Bayesian shrinkage priors for large dimensional multivariate models, including the horseshoe (Carvalho et al., 2009, Carvalho et al., 2010), priors which fall in the Least absolute shrinkage and selection operator (Lasso) class (Tibshirani, 1996); (Hastie et al., 2015) , the stochastic search variable selection (SSVS) prior (George and McCulloch, 1993, George and McCulloch, 1997) and adaptive shrinkage Jeffreys' and the Dirichlet–Laplace (D-L) prior of Bhattacharya et al. (2015). Following Gefang et al. (2023), we adopt D-L prior for parameter shrinkage because it has a nice theoretical property that the joint posterior distribution of the parameters concentrates at the optimal rate. In addition, D-L prior only requires a single prior hyperparameter, which makes prior sensitivity analysis a lot more straightforward.

As detailed in Ormerod and Wand (2010) and Blei et al. (2017), when the posteriors can be drawn from a Gibbs sampler, as in our case, appropriate densities from a mean field variational family can be used to approximate the posterior densities through minimizing the Kullback-Leibler divergence, which is equivalent to maximising the evidence lower bound. This approximation approach is called VB. VB is super-fast, hence more suitable to estimate complex models with a large number of parameters which are either impossible or too costly to estimate using Gibbs sampler. In our empirical work, we use VB approximation densities introduced in GHT to draw the conditional posteriors.

5. Results and data

5.1. The data

In what follows, we implement the Bayesian technique discussed above to our large VAR involving spatial spillovers among the three regions using all the variables which were in the original VAR of Hall et al. (2023). The data are monthly and seasonally adjusted (where necessary). The estimation period runs from January 1999 to April 2022. (The data definitions for each area are given in the data appendix, Appendix A.) Our model differs slightly from the standard VAR procedure because the variables for each region are slightly different due to data incompatibilities. For the US, we include the rate of change in the log of M2, the ratio of government spending to GDP, the rate of change in the log of Brent crude oil prices, the rate of change in the log of real GDP, the long-term interest rate, and a supply chain index, which tracks global supply constraints.[4] For the euro area, we use the change in the log of M3, the change in the log of Brent crude oil prices, the change in the log of industrial production, the unemployment rate, the euro/U.S. dollar exchange rate (in logs), and the supply chain index. For the U.K., the model includes the change in the log of M3, the change in the log of Brent crude oil prices, the long-term interest rate, the change in the log of wages, the ratio of the fiscal deficit to GDP, and the supply chain index.

5.2. The results of basic impulse responses

For the combined model we choose a maximum lag length of 7 based on stability criteria and the usual information criteria. We will not present the full spatial-VAR results because of the large number of coefficients, which, individually, are of little interest. However, as a starting point, it will be useful to look at the initial impact, spatial effects in each region's inflation equation for each of the other inflation terms. Of course, this is only a partial analysis, but it is indicative of the direct pass through. In other words, we are presently dealing with the impact effect rather than full solution to the dynamic VAR, the results of which we present subsequently. Table 1 shows the contemporaneous coefficient for each of the three regions on inflation in the other regions. This is only a small part of the unrestricted spatial weighting matrix, which is extremely large. The full unrestricted spatial weighting matrix is 21x21, that is, it includes 441 estimated parameters, with zero restrictions on own region effects.[5]

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[4] The global supply chain index is that constructed by the New York Fed. See Appendix 1.

Table 1. The impact of spatial effect in each equation for inflation.

Variables	**U.S. equation**	**Euro area equation**	**U.K. equation**
U.S.	0.00	0.1045 (0.0444)	0.0942 (0.0534)
Euro area	0.0659 (0.0234)	0.00	0.0838 (0.0361)
U.K.	0.0506 (0.0204)	0.0742 (0.0263)	0.00

Standard errors in parentheses.

As reported in Table 1, in the U.S. inflation equation, contemporaneous euro area inflation has a coefficient of 0.0659 while the U.K. coefficient is 0.0506. In other words, a one percentage point shock to euro area inflation raises U.S. inflation by about 0.066 percentage point during the month in which the shock occurred; a one percentage point shock to U.K. inflation raises U.S. inflation by 0.05 percentage point in the same month. Similarly, in the euro area equation, a one percentage point shock to U.S. inflation has a contemporaneous impact of 0.10 percentage point on euro area inflation (roughly twice the size of the effect of the euro area on the U.S.); the effect of a one percentage point shock to U.K. inflation raises euro area inflation by 0.0742 – somewhat less than the U.S. effect. Finally, in the last column, the U.S. has an effect of 0.0942 and the euro area has an effect of 0.0838 on U.K. inflation. We emphasise that the results in Table 1 are only a small part of the total spatial weighting matrix. There would also be contemporaneous effects from all the other variables in the complete VAR from each region on the other regions.

5.3. Impulse responses with a common shock

To fully understand the behaviour of our spatial-VAR, we need to turn to a full set of impulse responses. We depart from the usual practise of applying a one standard deviation shock to a variable. Instead, we apply a one-unit shock. Our reason for doing this is because we are interested in comparing the relative size of spillovers among the three regions. If we applied different shocks to each region, the spillovers may be different simply because of the application of different shocks.

The results are presented in the following figures, which show the effects of shocks to the price level and interest rates in each region on the price level and interest rates in the other two regions. This procedure allows us to show the full dynamics estimated in the VAR as well as the full unrestricted spatial weighting matrix, which, as noted, is a 21x21 matrix. The initial set of figures below concentrate on a unit shock to inflation in each region and the total spillover effects of that shock on the other regions. These figures capture a very complex interaction. For example, when we shock any U.S. variable, all the US variables will begin to adjust. These will then have direct effects on the other two regions. Thus, a shock to inflation in the U.S. will change all the other U.S. variables. These will then have direct contemporaneous effects on all the variables in the euro area and the U.K. Over time, this will set-off spillover effects from the U.K. and the euro area back to the U.S. and so on, thus building up a very rich and complex set of dynamic interactions.

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[5] There are two types of zero restrictions in the spatial weighting matrix. The own regional variables have zero restrictions, which is standard in spatial modelling. There are also zero restrictions where the same variable is used across different regions, for example, the oil price and the supply chain index appear in all regional VARs and hence must have a zero restriction in the spatial matrix

Given the complexity of our model, we cannot present all possible impulse responses here, but to provide the flavour of the extent and importance of the spillovers among the three regions, we show the effect on each region of a shock to the price level, the long term interest rate and the money supply on the other regions. The results are shown in Fig. 1, Fig. 2, Fig. 3, Fig. 4, Fig. 5, Fig. 6, Fig. 7, Fig. 8, Fig. 9. In particular, these figures show the effects of a constant shock to each region so that the effects of spillovers can be compared.

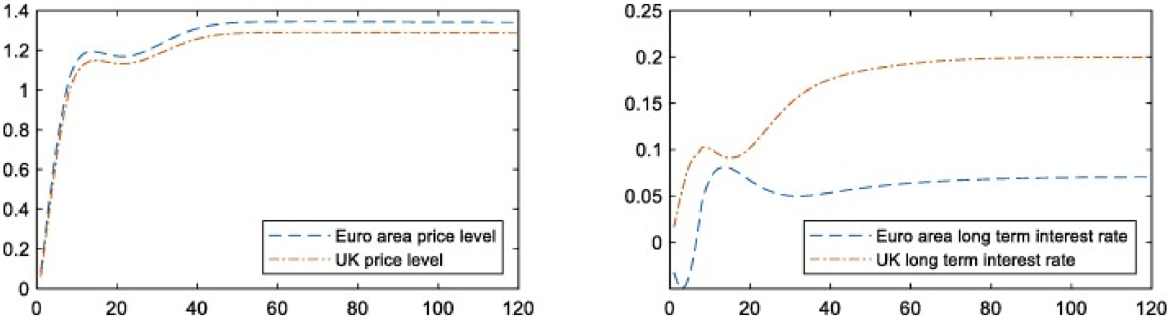

Fig. 1. The cumulative spillover effects of a sock to US prices.

Fig. 1 shows the cumulative spillover effects of a one percentage point shock to U.S. prices on the price levels and the interest rates in the euro area and the U.K. A one percentage point shock to U.S. prices produces a larger than unit long-run effect on the price level in the U.K. and the euro area. Specifically, a one percentage point shock to U.S. prices raises both euro area and U.K. prices by about 1.2 percentage points after about 12 months, and by about 1.4 percentage points in the long run. The greater-than-unity effect reflects the fact that in the full VAR, U.S. prices would have continued to rise after the shock. Thus, the total effect in the U.S. would have been considerably greater than the initial shock of 1 percentage point. We also see that the effect of a shock to U.S. prices is to raise interest rates in both the U.K. and the euro area: the peak effect on euro area interest rates is about 10 basis points; for the U.K. the peak effect is about 20 basis points.

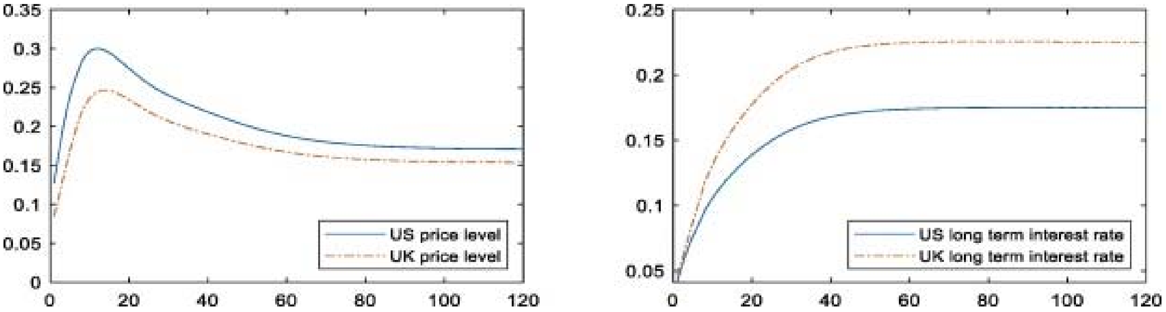

Fig. 2. The cumulative spillover effects of a shock to Euro area prices.

Fig. 2 reports the effects of a one-percentage point shock to the euro area's price level. The effect is much smaller on the U.S. price level than the effect from the U.S. on the euro area. The peak effect on the U.S. price level is about 0.3 percentage point after about 18 months; the long run effect is about 0.2 percentage point. The peak effect on the U.K. price level is about 0.25 percentage point after 18 months; the long run effect on U.K. prices is about 0.2 percentage point. The shock in the euro area does cause interest rates to rise in both the U.S. and the U.K. and by a similar amount to the U.S. effect reported in Fig. 1.

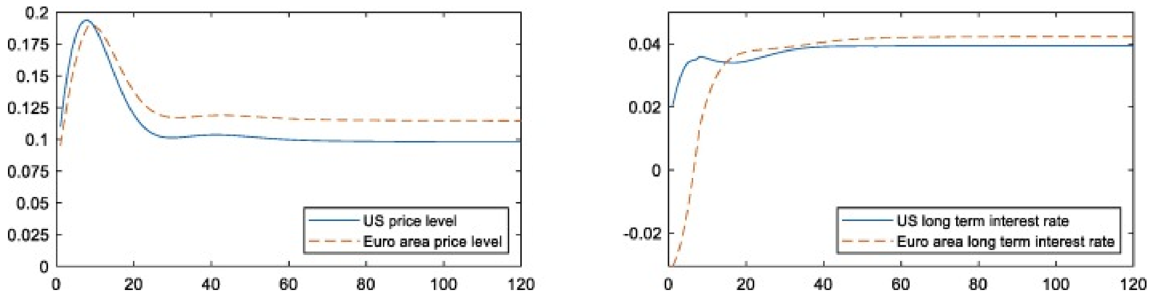

Fig. 3. The cumulative spillover effects of a shock to UK prices.

Fig. 3 reports the effects of a one percentage point shock to the U.K. price level. Here we see that a shock to prices in the U.K. has much smaller effects on the price level and the interest rates in both the U.S. and the euro area, but of the same sign as the effects from shocks to the price levels of the U.S. and the euro area.

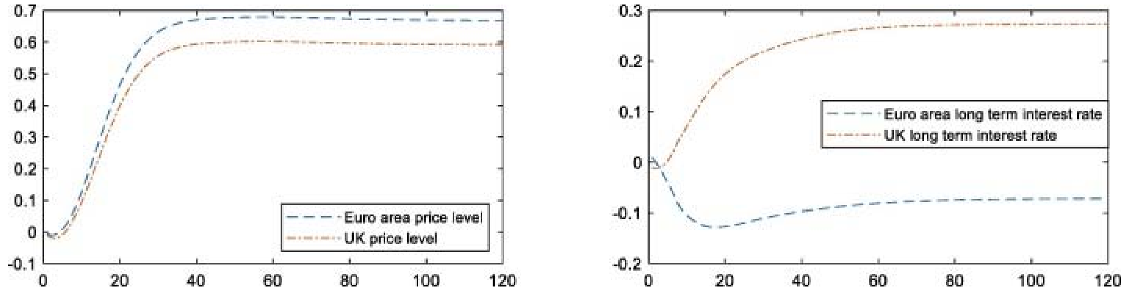

Fig. 4. The cumulative spillover effects of a shock to US Money supply.

Fig. 4 shows that effects of a one percentage point shock to the U.S. money supply (M2) on prices and interest rates in the other two regions. The effects on interest rates are, however, small and negative in the case of the euro area. The effects are small and positive in the case of the U.K.

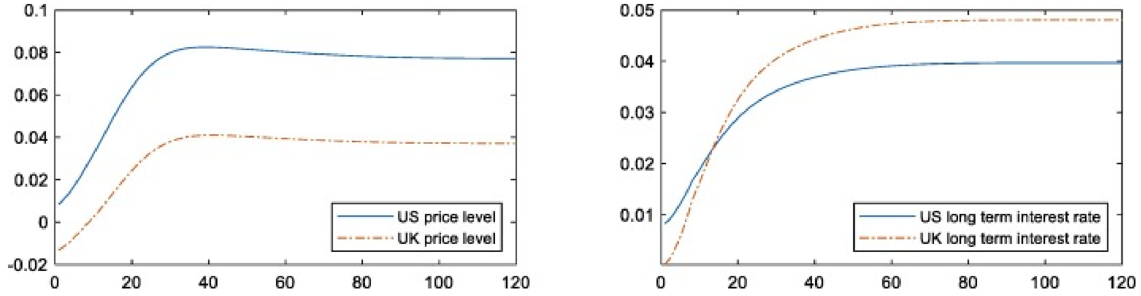

Fig. 5. The cumulative spillover effects of a shock to Euro area Money supply.

Fig. 5 shows the effects of a one percentage point shock to the euro area money supply (M3). The effect of the shock is to raise the price level in both the U.S. and the U.K., but by an order of magnitude less than the reciprocal effect of a shock to the U.S. money supply. Both U.S. and U.K. long-term interest rates rise, but only by very small amounts.[6]

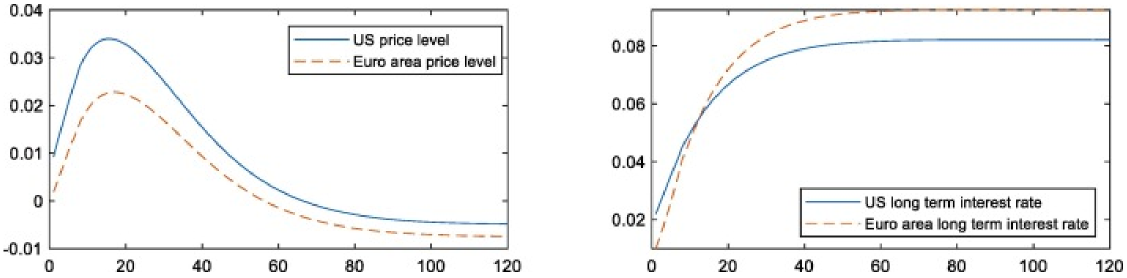

Fig. 6. The cumulative spillover effects of a shock to UK Money supply.

Fig. 6 shows the effects of a one percentage point shock to the U.K. money supply (M3). The shock produces small and transitory effects on prices in the other two regions. The effects on interest rates in the other two regions are also small but the effects persist in the long run.

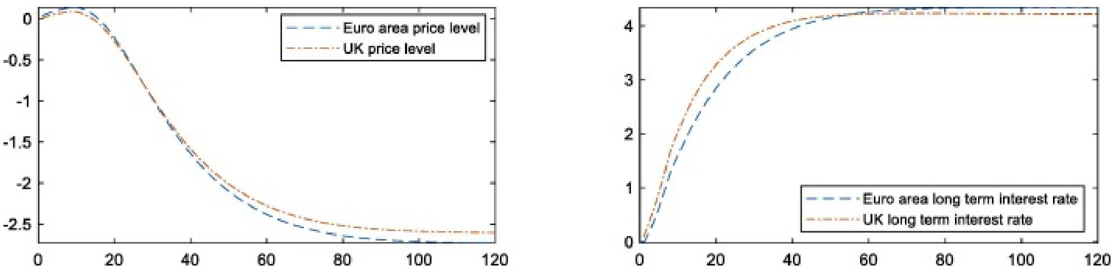

Fig. 7. The cumulative spillover effects of a shock to US long term interest rate.

Fig. 7 shows the cumulative effects of a one percentage point shock to the U.S. 10-year government bond rate. Here we see that an increase in U.S. long-term interest rates causes a permanent reduction in both the U.K. and euro area price levels. The euro area price level falls by about 2.5 percentage points after 5 years; the U.K. price level falls by about 2.5 percentage points after 7 years. Because of the dynamics in the VAR, the one percentage point shock to U.S. interest rate produces growing effects on U.S. interest rate over time, which feed into U.K. and euro area interest rates in the long run. Consequently, U.K. and euro area interest rates rise for about four years, with the long impact peaking at about 4 percentage points for both regions.

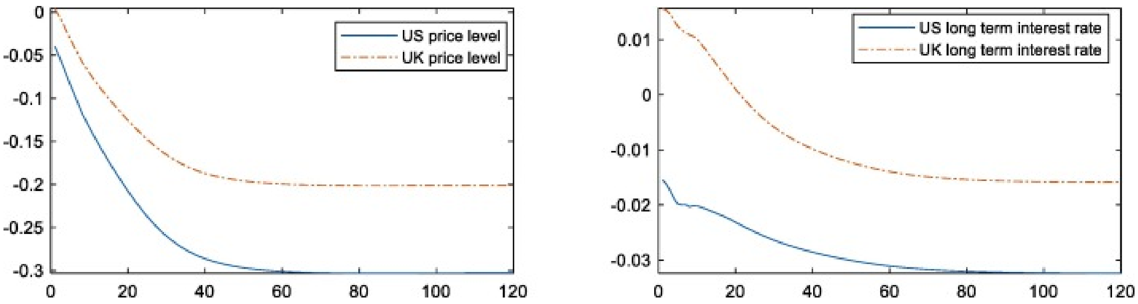

Fig. 8. The cumulative spillover effects of a shock to Euro area long term interest rate.

In Fig. 8, we show the effects of a one percentage point shock to euro area 10-year government bond rates. Here, the effect of a positive shock has a similar effect on both the U.S. and U.K. price levels, but it is much smaller than the reciprocal effect from the U.S. In this case, both the U.S. and the U.K. see an eventual very small fall in their long term interest rates.

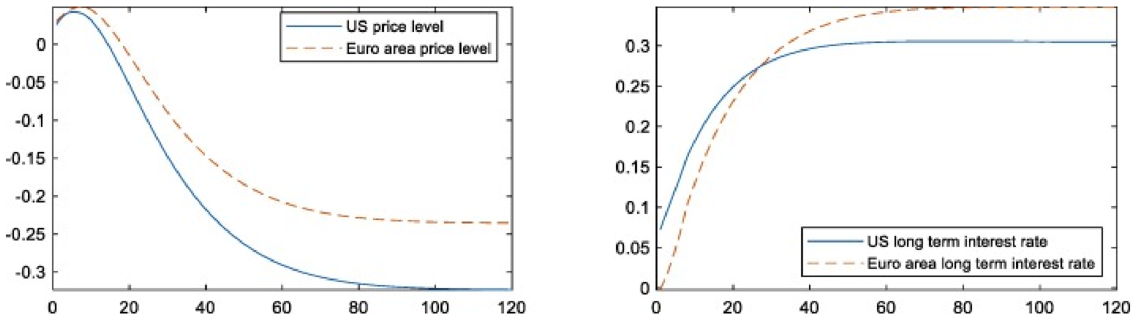

Fig. 9. The cumulative spillover effects of a shock to UK long term interest rate.

Fig. 9 reports the effects of a one percentage point shock to U.K. long-term interest rates. Prices in both the U.S. and the euro area fall by small amounts. There is a small positive effect on long-term interest rates in both the U.S. and the euro area of similar magnitude.

We can of course go on to shock any of the other variables in each region and investigate its effects on the other two regions. But the foregoing impulse responses show a very clear dominance in terms of spillovers from the U.S. to the other two regions. The euro area has some effects on the U.S. and a slightly larger effect on the U.K., but these effects are always much smaller than the U.S. effects. Generally speaking, the U.K. has a much smaller impact than the U.S. and a somewhat smaller impact than the euro area.

5.4. Impulse responses based on 'Realistic' shocks

In this section, we focus on the inflationary period beginning in 2020. Instead of using standard impulse responses with an arbitrary shock to the VAR's, we calibrate the shock so as to reproduce the actual behaviour seen in certain variables as a result of Covid and the Ukraine war. This procedure differs from the usual analysis in that we now address the following type of issue: what has been the effect of, for example, the rapid rise in U.S. money supply following Covid on the euro area and the U.K. The way we do this is to calculate a shock to a variable which makes the regional VAR reproduce what actually happened during the key point of the recent inflationary period. We then run the full spatial VAR subject to this shock, which allows us to calculate spillovers to the other regions. The details of the actual shocks we apply are presented in Appendix B.

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[6] Note that the euro area price level goes up and long term interest rates go down following a positive shock to the U.S. money supply, while the U.S. price level and long term interest rates go up following a positive shock to the euro area money supply. The different movements in interest rates is due to the varying strengths of spillovers between the two regions. Generally, when the money supply increases we would expect interest rates to fall, but if inflation rises we might expect interest rates to rise. The net effect can, therefore, go either way depending on the relative speed of responses and spillover effects.

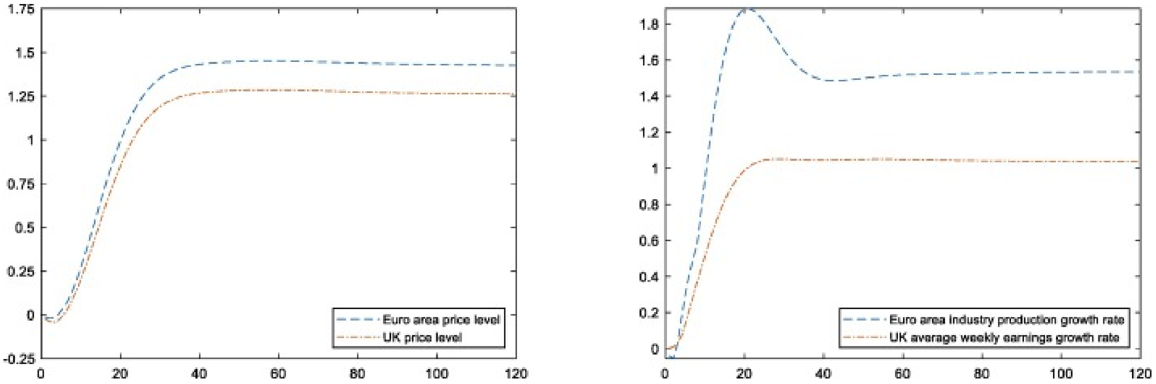

Fig. 10. The cumulative spillover effects of a shock to US money supply (cause US M2 growth rate to increase by 5 % after one year).

In the U.S., M2 rose very rapidly, by 5 percentage points, after the onset of COVID and lockdown. Fig. 10 shows the spillovers from this shock to the euro area and the U.K.

We can see that for the first 3–4 months, there was very little spillover effects on the euro area and U.K. prices. There were, however, fairly rapid rises in the spillover over the next 2 years producing an overall increase in the price level in these regions of around 1.25 percentage points. We also show that industrial production in the euro area was 1.5 percentage points higher than it would otherwise have been after about 3 years and U.K. wages were about 1 percentage point higher after 2 years.

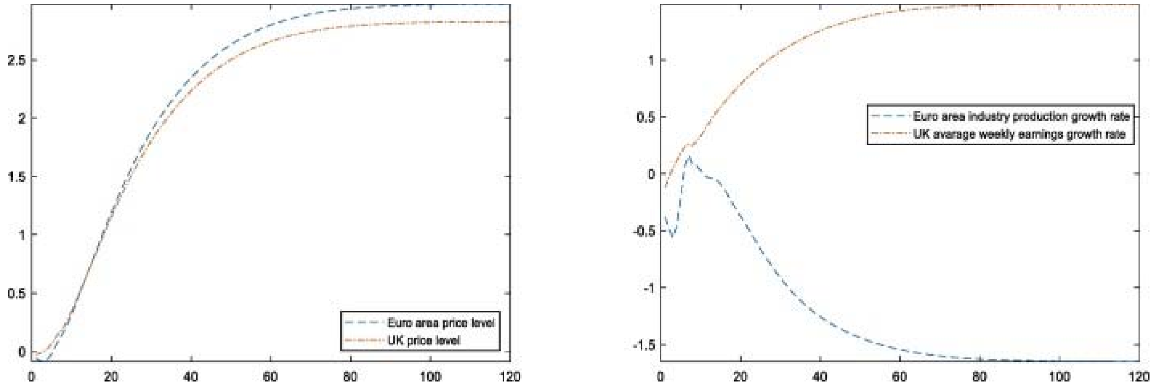

Fig. 11. The cumulative spillover effects of a shock to US Government spending (thatraises US spending to GDP ratio by 10 % in 18 months).

Fig. 11 shows the spillovers which were caused by the very rapid rise in U.S. government expenditure to GDP ratio. In particular, the support packages due to COVID produced a very rapid rise in this ratio of around an extra 10 percentage points.

In Fig. 11, the large rise in the U.S. government spending to GDP ratio has a steady and long lasting impact on prices in both the U.K. and the euro area which steadily raises the price level by around 2.4 percentage points over 5 years. It is interesting that U.K. wages lag behind prices and only rise by about 1 percentage point. Industrial production in the euro area falls over a similar time horizon by around 1.5 percentage points.

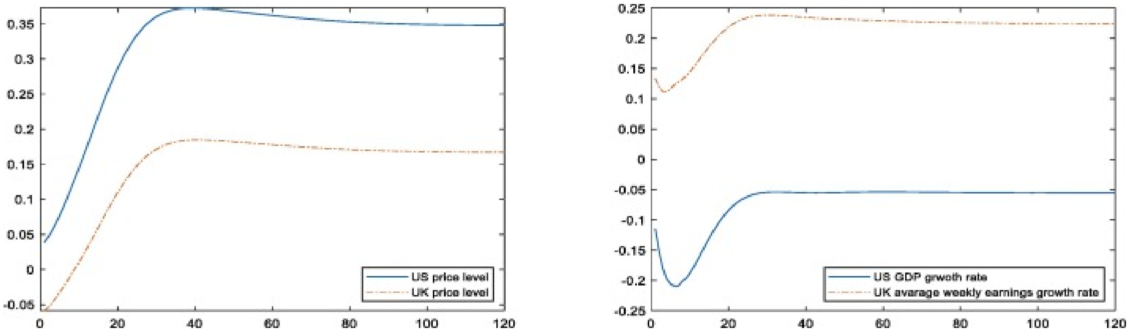

Fig. 12. The cumulative spillover effects of a shock to Euro area M3 (that increase its annual growth rate by 10 % points after a year).

We now turn to the spillovers from the euro area to the U.S. and the U.K. During the Covid pandemic, euro area M3 increased by 5 % over the course of a year. We calculate the shock which would produce this in the euro area. Fig. 12 shows the spillovers into the U.S. and the U.K. The figure shows that the shock to euro area money supply produced an increase in U.S. prices of around 0.35 percentage point and just under 0.2 percentage point for the U.K. U.S. real GDP growth was reduced by about 0.05 %. So the spillovers from the euro area into the U.S. and the U.K. were quite small.

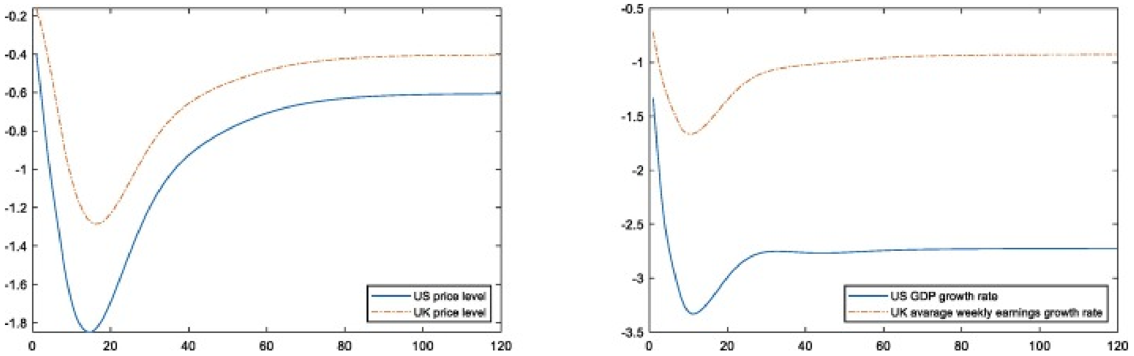

Fig. 13. The cumulative spillover effects of a shock to Euro area industrial production (that reduces its growth rate by 30 % in 4 months).

Fig. 13 shows the effect of a shock which reduces euro area industrial production by 30 % over 4 months. This is obviously a very large effect and its longer term effects may not be realistic since this shock was quite quickly reversed and industrial production returned to near normal levels quite rapidly. In the VAR simulation, however, industrial production was down for quite a long period. As shown in the figure, U.S. and U.K. prices fell by around 2 % and 1.5 %, respectively, after 18 months. U.S. GDP growth was permanently reduced and U.K. wages were also permanently reduced.

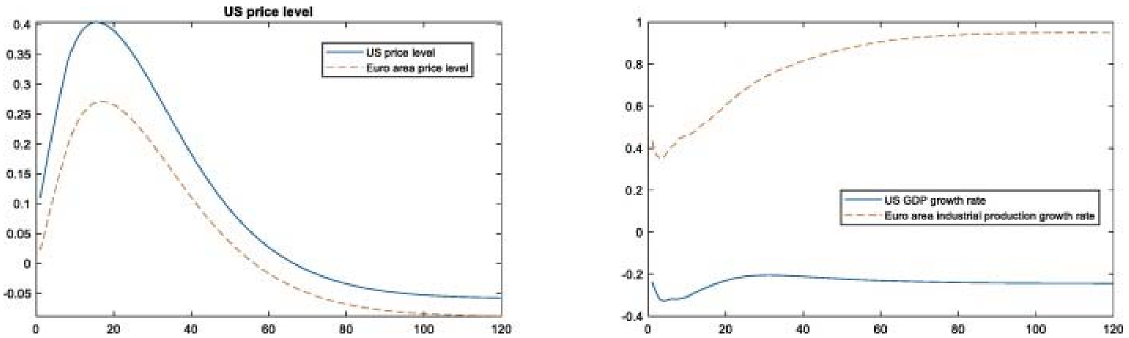

Fig. 14. The cumulative spillover effects of a shock to UK Money Supply (that increases its growth rate by 12 % in 3 months).

We now turn to the U.K. Fig. 14 shows the effect of a shock to U.K. M3., which increased the stock of money by 12 % points after 3 months. Although the shock in the U.K. was quite large, the effects on the U.S. and euro area were small. The U.S. price level rose by a little more than the euro area but both then decline to zero over time. U.S. GDP growth was somewhat reduced while euro area industrial production rose by a small amount.

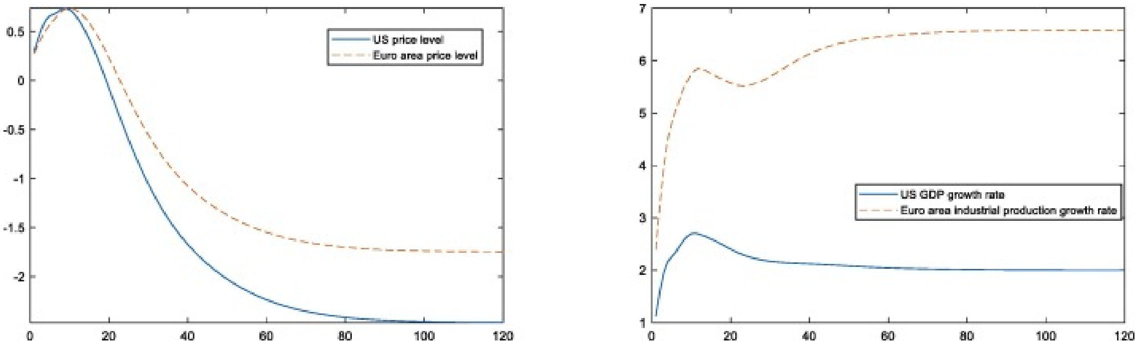

Fig. 15. The cumulative spillover effects of a shock to UK government spending (that increases it by 24 % points after 12 months).

Finally, in Fig. 15 we see the effect of a shock to the U.K. government deficit to GDP ratio which rose by 24 % over 12 months. The shock produced an initial small increase in both the U.S. and the euro area price levels, but over time this turns into a small fall in prices. U.S. GDP and euro area industrial production both grew somewhat over the first 2 years.

To further demonstrate the effect of these realistic shocks, we now summarise a range of spillovers showing effects of these shocks on each region on the price levels in the other two regions. The results are reported in Table 2, Table 3, Table 4. The tables report the effects of shocks after 24 months and the peak effects of the shocks. The particular shocks are applied to each of the variables in each VAR. In what follows, we confine our discussion to shocks on price levels.

Table 2. Effects on the U.S. Price Level of Realistic Shocks to the Euro Area and the U.K.

	After 24 months	**Peak effect**	**Peak month**
Euro area price level	1.31	1.52	12
U.K. price level	0.57	1.05	8
Euro area M3	0.33	0.37	39
Euro area long-term interest rate	−0.23	−0.04	1
Euro area industrial production	−1.48	−0.40	1
Euro/US dollar exchange rate	−1.85	2.56	6
U.K. M3	0.36	0.40	15
U.K. long-term interest rate	−0.09	0.04	5
U.K. government deficit	−0.51	0.74	9

Table 2 reports the effects on the U.S. price level of realistic shocks to key variables in the euro area and the U.K. For example, a realistic shock to the euro area price level – that is a shock that would have raised euro area prices by the amounts that actually occurred from 2020:1 to 2022:4 – would have raised U.S. prices by 1.31 percentage points after 24 months. The peak effect – 1.52 percentage points – occurred after 12 months. Correspondingly, a realistic shock to the U.K. price level during the same period would have raised U.S. prices by 0.57 percentage point after 24 months. The peak effect – 1.05 percentage points – occurred after 8 months. Similar, interpretations apply to the effects of the other shocks to euro area and U.K. variables reported in Table 2.

Table 3. Effects on the Euro Area Price Level of Realistic Shocks to the U.S. and the U.K.

	After 24 months	**Peak effect**	**Peak month**
U.S. price level	3.90	4.46	70
U.K. price level	0.67	1.03	9
U.S. M2	1.19	1.45	58
U.S. long-term interest rate	−0.29	0.08	9
U.S. real GDP	−0.02	0.00	1
U.S. government expenditure	1.50	2.98	121
U.K. M3	0.25	0.27	17
U.K. long-term interest rate	−0.04	0.05	7
U.K. government deficit	−0.10	0.74	10

Table 3 reports the effects on the euro area of realistic shocks to key variables in the U.S. and U.K. As reported in the table, a shock to the U.S. price level raises euro area prices by 3.9 percentage points. To provide specific content, the results indicate that the rise in the U.S. price level contributed 3.9 percentage points to the rise in the euro area price level in the 24 months ending in April 2022. The effects on the euro area price level of the rise in the U.K. price level were much smaller – 0.67 percentage point after 24 months.

Table 4 reports the effects on the U.K. price level of realistic shocks to key variables in the U.S. and the euro area. Again, the results indicate that a realistic shock to the U.S. price level had a very large effect on the U.K. price level – 3.77 percentage points after 24 months. A realistic shook to the euro area price level is shown to have raised the U.K. price level by 1.13 percentage points after 24 months.

Table 4. Effects on the U.K. Price Level of Realistic Shocks to the U.S. and the Euro Area.

	After 24 months	Peak effect	Peak month
U.S. price level	3.77	4.28	69
Euro area price level	1.13	1.25	14
U.S. M2	1.03	1.29	58
U.S. long-term interest rate	−0.30	0.05	9
U.S. real GDP	−0.01	0.00	1
U.S. government expenditure	1.44	2.83	121
Euro area M3	0.14	0.18	41
Euro area long-term interest rate	−0.14	0.00	1
Euro area industrial production	−1.10	−0.16	1
Euro/U.S. dollar exchange rate	0.23	6.05	7

The above pattern in which shocks to the U.S. price level have much larger impacts on the euro area and U.K. price levels than the reverse effects of shocks to euro area and U.K. price levels is evident for other shocks reports in Table 2, Table 3, Table 4. Consider, for example, a shock to monetary policy as represented by a shock to money growth. The effect of a realistic shock to U.S. M2 growth raises the price levels in the euro area and the U.K. by 1.19 percentage points and 1.03 percentage points after 2 years, respectively. A realistic shock to euro area M3 growth raises the U.S. price level by 0.33 percentage point and the U.K. price level by 0.14 percentage point, respectively, after 2 years. A realistic shock to the U.K. price level raises the price levels in the U.S. and the euro area by 0.57 percentage point and 0.25 percentage point, respectively – again after 2 years. As reported in Table 2, Table 3, realistic shocks to U.S. government expenditure (as a percentage of GDP) have especially large impacts on euro area and U.K. price levels – 1.50 percentage points and 1.44 percentage points, respectively, after 2 years.

In sum, we have proposed a new estimation method that allows fully endogenous interactions among all the variables in a number of separate models. The application of our method allowed us to estimate spillover effects of all variables in the VAR.

6. Conclusions

We have proposed a new spatially augmented VAR. To implement our procedure, we applied it to three regions, the U.S., the euro area and the U.K. This model involves a potentially large number of spatial parameters. In our model, it is a 21x21 matrix of spatial weights. The use of the standard approach in spatial modelling of specifying a pre-determined weighting matrix would not have fulfilled our objective, which was explicitly to investigate the relative size of these weights. To address this issue, we implemented a new Bayesian estimation technique which allows us to freely estimate these weights. This technique would be applicable to many standard spatial models and would negate the need to impose fixed pre-determined weights on these models.

We then proceeded to estimate our full spatially augmented VAR for the three regions. We found that there were much stronger spillover effects from the U.S. to the other two regions with only much weaker spillovers from the U.K. and the euro area back to the U.S. The impact of a shock to the euro area on the U.K. and the U.S. was generally larger than the U.K. shock on the euro area and the U.S., but nevertheless was considerably smaller than the shock to the

U.S. We then calibrated a set of realistic shocks which mimicked the unusual shocks that took place in 2020 and 2021. We showed that the estimated spillovers resulted from these shocks.

The concept of a spatially augmented VAR could have potentially very wide applications in dealing with a set of equations for a particular cross section unit – for example, an individual country, firm, or region – in a panel setting in which the researcher is interested in quantifying spillover effects among the units. The SESAR model does this to some extent but it is subject to the unrealistic assumption of a fixed weighting matrix and, thus, is subject to the usual problems of structural identification which Sims (Sims, 1972, Sims, 1980) originally designed the VAR to overcome. Our spatially augmented VAR may be thought of as a VAR alternative to the SESAR model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Data definitions

Data for the U.S.

CPI	Consumer Price Index: Total All Items for the United States, Index 2015 = 100, Monthly, Seasonally Adjusted, https://fred.stlouisfed.org/series/CPALTT01USM661S
Ex. EUUS	Euro to US dollar exchange rate, Average https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
Ex. UKUS	U.S. Dollars to U.K. Pound Sterling exchange rate, average https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
expinf	Inflation forecast is measured in terms of the consumer price index (CPI). Source expected inflation, OECD, https://data.oecd.org/price/inflation-forecast.htm
govdef	U.S. Government deficit as a percentage of nominal GDP https://fred.stlouisfed.org/series/FGLBAFQ027S
govspend	Final Government expenditure as a percentage of nominal GDP, https://fred.stlouisfed.org/series/W068RCQ027SBEA
ip	Industrial Production: Total Index, Index 2017 = 100, Seasonally Adjusted, https://fred.stlouisfed.org/series/INDPRO
ltir	Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Percent, https://fred.stlouisfed.org/series/GS10
m2	U.S., M2, Billions of Dollars, Monthly, https://fred.stlouisfed.org/series/M2NS
nairu_lt	Noncyclical Rate of Unemployment, Percent, Quarterly, Not Seasonally Adjusted https://fred.stlouisfed.org/series/NROU
nairu_st	Natural Rate of Unemployment (Short-Term) (DISCONTINUED), Percent, Quarterly, Not Seasonally Adjusted https://fred.stlouisfed.org/series/NROUST
oil_brent	Crude Oil Prices: Brent – Europe, Dollars per Barrel, Monthly, https://fred.stlouisfed.org/series/DCOILBRENTEU
oil_wti	Crude Oil Prices: West Texas Intermediate (WTI) – Cushing, Oklahoma, Dollars per Barrel, Monthly, https://fred.stlouisfed.org/series/DCOILWTICO

outgap	The output gap. Estimated by Kathryn Holston, Thomas Laubach, and John C. Williams, Journal of International Economics, 2017, “Measuring the Natural rate of Interest: International Trends: International Trends and Determinants”
rgdp	National Accounts, Expenditure, Gross Domestic Product, Real, Seasonally Adjusted, Domestic Currency, in millions, https://data.imf.org/?sk=4C514D48-B6BA-49ED-8AB9-52B0C1A0179B&sId=1390030341854
stir	3-Month Treasury Bill Secondary Market Rate, Percent, Monthly, Not Seasonally Adjusted, https://fred.stlouisfed.org/series/TB3MS
supply chain index	A supply chain index constructed by the Federal Reserve Bank of New York. It measures the level of disruption in the world’s supply chain: Federal Reserve Bank of New York, Global Supply Chain Pressure Index, https://www.newyorkfed.org/research/gscpi.html
unrate	Unemployment Rate, Percent, Monthly, Seasonally Adjusted, https://fred.stlouisfed.org/series/UNRATE
wage	Employed full time: Median usual weekly nominal earnings (second quartile): Wage and salary workers: 16 years and over, Dollars, Quarterly, Interpolated to monthly, https://fred.stlouisfed.org/series/LES1252881500Q

Data for the Euro Area.

CPI	Consumer Price Index: Harmonized Prices: Total All Items for the Euro Area, Index 2015=
Ex. EUUK	Euro to UK pound sterling exchange rate, Average, https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
Ex. EUUS	Euro to US dollar, Average, https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
Expinf	Inflation forecast is measured in terms of the consumer price index (CPI). Source expected inflation, OECD, https://data.oecd.org/price/inflation-forecast.htm
govdef	Euro area 19 (fixed composition) as of 1 January 2015 – Net lending (pos) / net borrowing (neg) – Balance (Credits minus Debits) – ratio to the annual moving sum of gross domestic product, Neither seasonally adjusted nor calendar adjusted – ESA 2010 https://sdw.ecb.europa.eu
govspend	Final consumption expenditure – Euro area 19 (fixed composition) – World (all entities, including reference area, including IO), General government, Euro, Current prices, Non transformed data, % of nominal GDP, https://sdw.ecb.europa.eu
ip	Euro area 19 (fixed composition) – Industrial Production Index, Total Industry – NACE Rev2; Eurostat; Working day adjusted, https://sdw.ecb.europa.eu
ltir	Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for Germany, Percent, Monthly, Not Seasonally Adjusted, https://fred.stlouisfed.org/series/IRLTLT01DEM156N
m3	M3 for the Euro Area, National Currency, Monthly, Not Seasonally Adjusted, https://fred.stlouisfed.org/series/MABMM301EZM189N
oil_brent	Crude Oil Prices: Brent – Europe, Dollars per Barrel, Monthly, https://fred.stlouisfed.org/series/DCOILBRENTEU
oil_wti	Dollars per Barrel, Monthly, https://fred.stlouisfed.org/series/DCOILWTICO

outgap	The output gap. Estimated by Kathryn Holston, Thomas Laubach, and John C. Williams, Journal of International Economics, 2017, “Measuring the Natural rate of Interest: International Trends: International Trends and Determinants”
stir	Euro area (moving concept in the Real Time database context) – Rate – 3-month Euribor (Euro interbank offered rate) – Euro, Average of observations through period, https://sdw.ecb.europa.eu
supply chain index	A supply chain index constructed by the Federal Reserve Bank of New York. It measures the level of disruption in the world’s supply chain: Federal Reserve Bank of New York, Global Supply Chain Pressure Index, https://www.newyorkfed.org/research/gscpi.html
unrate	Euro area 19 (fixed composition) as of 1 January 2015; European Labor Force Survey; Unemployment rate; Total; Age 15 to 74; Total; Seasonally adjusted, not working day, https://sdw.ecb.europa.eu

Data for the U.K.

CPI	Consumer Price Index of All Items in the United Kingdom, Index 2015 = 100, Monthly, Not Seasonally Adjusted, https://fred.stlouisfed.org/series/GBRCPIALLMINMEI
Ex. EUUK	Euro to UK pound sterling exchange rate, Average, https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
Ex. UKUS	U.S. Dollars to U.K. Pound Sterling exchange rate, Average, https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
expinf	Inflation forecast is measured in terms of the consumer price index (CPI). Source expected inflation, OECD, https://data.oecd.org/price/inflation-forecast.htm
govdef	Government deficit, Net lending (+)/net borrowing (−) as a percentage of GDP – General government, https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/ct8o/ukea
govspend	Nominal General Government Final Consumption Expenditure for Great Britain, Domestic Currency, Quarterly, interpolated to monthly and expressed as a percentage of nominal GDP, https://fred.stlouisfed.org/series/NCGGSAXDCGBQ
ip	Production of Total Industry in the United Kingdom, Index 2015 = 100, Monthly, Seasonally Adjusted, https://fred.stlouisfed.org/series/GBRPROINDMISMEI
ltir	Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the United Kingdom, Percent, Monthly, Not Seasonally Adjusted, https://fred.stlouisfed.org/series/IRLTLT01GBM156N
m0	Monthly average amount outstanding of total sterling notes and coin in circulation, excluding backing assets for commercial banknote issue in Scotland and Northern Ireland, https://www.bankofengland.co.uk/boeapps/database/BankStats.asp
m1	Monthly amounts outstanding of monetary financial institutions’ sterling and all foreign currency M1 (UK estimate of EMU aggregate) liabilities to private and public sectors (in sterling millions) not seasonally adjusted, https://www.bankofengland.co.uk/boeapps/database/BankStats.asp

Monthly amounts outstanding of monetary financial institutions’ sterling and all foreign currency M1 (UK estimate of EMU aggregate) liabilities to private and public sectors, https://www.bankofengland.co.uk/boeapps/database/BankStats.asp

m2	Monthly amounts outstanding of monetary financial institutions’ sterling and all foreign currency M2 (UK estimate of EMU aggregate) liabilities to private and public

	sectors (in sterling millions) not seasonally adjusted https://www.bankofengland.co.uk/boeapps/database/BankStats.asp
m3	Monthly amounts outstanding of monetary financial institutions' sterling and all foreign currency M3 (UK estimate of EMU aggregate) liabilities to private and public sectors (in sterling millions) not seasonally adjusted https://www.bankofengland.co.uk/boeapps/database/BankStats.asp
oil_brent	Crude Oil Prices: Brent – Europe, Dollars per Barrel, Monthly, https://fred.stlouisfed.org/series/DCOILBRENTEU
oil_wti	Dollars per Barrel, Monthly, https://fred.stlouisfed.org/series/DCOILWTICO
outgap	The output gap. Estimated by Kathryn Holston, Thomas Laubach, and John C. Williams, Journal of International Economics, 2017, "Measuring the Natural rate of Interest: International Trends: International Trends and Determinants"
rgdp	Real GDP, National Accounts, Expenditure, Gross Domestic Product, Real, Seasonally Adjusted, Domestic Currency, in millions, https://data.imf.org
stir	Short term interest rate, 3-Month or 90-day Rates and Yields: Interbank Rates for the United Kingdom, Percent, Monthly, Not Seasonally Adjusted, https://fred.stlouisfed.org/series/IR3TIB01GBM156N
supply chain index	A supply chain index constructed by the Federal Reserve Bank of New York. It measures the level of disruption in the world's supply chain: Federal Reserve Bank of New York, Global Supply Chain Pressure Index, https://www.newyorkfed.org/research/gscpi.html
unrate	Unemployment rate (aged 16 and over, seasonally adjusted), https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/timeseries/mgsx/lms
wage	Average Weekly Earnings: Whole Economy Level (£): Seasonally Adjusted Total Pay Excluding Arrears, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/timeseries/kab9/emp

Appendix B. The definition of the 'Realistic' shocks

The idea behind these shocks is that we are trying to estimate the spillovers which actually occurred during the period 2020–22 as Covid and then the Ukraine war affected the world economy. The way this is done is to look at a particular variable and the way it evolved over the crises period. We then apply a shock to that variable in the complete spatial VAR which is calibrated to reproduce the effect on that particular variable. The following list gives the details of the behaviour we are replicating for each variable.

U.S.:

- A shock to U.S. price level causing it to increase by 7 % after 12 months
- A shock to U.S. M2 growth rate causing it to increase by 5 % after one year
- A shock to U.S. long-term interest rate causing it to increase by 2 % after 24 months
- A shock to U.S. real GDP causing it to drop 5 % after 6 months
- A shock to the U.S. government expenditure to GDP ratio causing 10 % increase in the ratio after18 months

Euro area:

- A shock to euro area price level causing it to increase by 8 % after 18 months
- A shock to euro area M3 growth rate causing it to increase by 5 % after one year
- A shock to euro area unemployment rate causing it to increase by 1 % after 12 months
- A shock to euro area industrial production that causes a fall of 30 % after 4 months
- A shock to Euro/U.S. dollar exchange rate causing it to increase by 4 after 12 months

U.K.:

- A shock to U.K. price level causing it to increase by 6 % after 12 months
- A shock to U.K. M3 growth rate causing it to increase by 12 % after 3 months
- A shock to U.K. long-term interest rate causing it to increase by 1 % after 4 months
- A shock to U.K. wages that causes an increase of 8.5 % after 12 months
- A shock to U.K. Gov deficit to GDP which raises the ratio by 24 % after 12 months

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