Koop, Gary and McIntyre, Stuart and Mitchell, James and Poon, Aubrey (2018) Regional Output Growth in the United Kingdom : More Timely And Higher Frequency Estimates,1970-2017. Discussion paper. Economic Statistics Centre of Excellence, London. ,

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ESCoE Discussion Paper 2018-14

November 2018

ISSN 2515-4664

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Regional Output Growth in the United Kingdom: More Timely and Higher Frequency Estimates, 1970-2017

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Abstract

Output growth estimates for the regions of the UK are currently published at the annual frequency only and are released with a long delay. Regional economists and policymakers would benefit from having higher frequency and more timely estimates. In this paper we develop a mixed frequency Vector Autoregressive (MF-VAR) model and use it to produce estimates of quarterly regional output growth. Temporal and cross-sectional restrictions are imposed in the model to ensure that our quarterly regional estimates are consistent with the annual regional observations and the observed quarterly UK totals. We use a machine learning method based on the hierarchical Dirichlet-Laplace prior to ensure optimal shrinkage and parsimony in our over-parameterised MF-VAR. Thus,this paper presents a new, regional quarterly database of nominal and real Gross Value Added dating back to 1970. We describe how we update and evaluate these estimates on an ongoing, quarterly basis to publish online (at www.escoe.ac.uk/regionalnowcasting) more timely estimates of regional economic growth. We illustrate how the new quarterly data can be used to contribute to our historical understanding of business cycle dynamics and connectedness between regions.

Keywords: Regional data, Mixed frequency, Nowcasting, Bayesian methods, Real-time data, Vector autoregressions

JEL classification: C32, C53, E37

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This ESCoE paper was first published in November 2018.

Regional Output Growth in the United Kingdom: More Timely and Higher Frequency Estimates, 1970-2017*

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November 15, 2018

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*The authors are grateful for comments on earlier versions of this paper from Ana Galvao, Hashem Pesaran, Martin Weale and colleagues at the Office for National Statistics, as well as seminar and conference participants at the ES-CoE/ONS/BoE Economic Measurement 2018 Annual Conference, the University of Southern California, Strathclyde University, Heriot Watt University and the National Institute of Economic and Social Research.

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1 Introduction

"That's your bloody GDP. Not ours." So famously shouted a Brexit heckler in Newcastle in response to an 'expert' predicting an economic slowdown in the UK post-Brexit (Chakrabortty, 2017). The Chief Economist at the Bank of England has similarly reflected on the apparently contrasting economic experiences of half a dozen local charities and community groups in Nottingham in the aftermath of the global financial crisis, asking "*whose* recovery were we actually talking about?". He then went on to emphasise the need to "disaggregate" the "economic jigsaw" to provide a more meaningful, including regionally disaggregated, picture of the UK economy (Haldane, 2016).

While many macroeconomic variables at the national (in our case, UK) level, including the main measures of economic activity such as Gross Domestic Product (GDP) and Gross Value Added (GVA)[1], are available at a monthly or quarterly frequency and are released fairly quickly, unfortunately official GVA data for the UK regions are currently only available from the Office for National Statistics (ONS) on an annual basis. Furthermore, these data are released with a delay of approximately a year and only date back, in their current form, to 1997/1998.[2] Thus, hecklers and policymakers alike have been obliged, if they want to understand local/regional developments, to use data which are out-of-date and offer limited historical coverage.

The purpose of this paper is to improve the regional database in the UK by developing and then using econometric methods to produce quarterly estimates of GVA growth for the twelve 'Nomenclature of Territorial Units for Statistics'[3] (NUTS) 1, or first-level, regions of the UK. Importantly this is done ensuring these new quarterly data are consistent with, and indeed condition on, both the annual data for the regions that are (and historically have been) published by the ONS and the quarterly data for the UK as a whole which they add up to. Using these econometric methods we produce historical quarterly estimates of regional GVA growth dating back to 1970. We also describe how we use and evaluate them on an ongoing, quarterly basis to produce more timely estimates (or 'nowcasts') of regional economic growth up to the present day. We demonstrate that accurate regional nowcasts can be produced using our econometric methods by timing their production so that they exploit - and importantly add up to - the latest quarterly estimates for UK growth as a whole. These historical and more timely data are all made available to researchers online.[4] These estimates are and will be updated each quarter on receipt of the latest UK data.

The ONS itself plans, over time, to fill some of the same information gaps that this paper seeks to address by publishing quarterly Regional Short Term Indicators from early 2019; and short-term indicators already exist for Northern Ireland and Wales, and, as discussed below, Scotland has, for some time, produced its own quarterly GVA estimates. Official estimates of regional output growth are, of course, to be preferred over model-based ones - if and when both sets of estimate are available. But our model-based approach, however, does and will continue to offer the advantage of facilitating the production both of more timely estimates (as the ONS's planned Regional Short Term Indicators

[1]Our model uses data on GVA rather than GDP, as GVA is the measure of economic growth available consistently at the regional level; the growth rates of real GVA and real GDP are the same. Recall, GVA plus taxes (less subsidies) on products equals GDP. For further details on the relationship between GDP and GVA see: https://www.ons.gov.uk/ons/rel/elmr/economic-trends--discontinued-/no--627--february-2006/methodology-notes--links-between-gross-domestic-product--gdp--and-gross-value-added--gva-.pdf

[2]In the summer of 2018 ONS changed its publication model and release calendars to release UK GVA (and GDP) at a monthly frequency. But historical estimates (prior to January 1997) of UK GVA at this monthly frequency are not available. As discussed below, the ONS also plan to publish quarterly Regional Short Term Indicators from early 2019.

[3]For an overview of the NUTS classification system, see: https://www.ons.gov.uk/methodology/geography/ukgeographies/eurostat

[4]See www.escoe.ac.uk/regionalnowcasting

will still be released with a longer delay of 3 to 4 months than equivalent quarterly data for the UK as a whole) and consistent quarterly historical data back to 1970.

The intuition underlying the econometric methods that we develop is that GVA growth for the UK regions is correlated with UK GVA growth (and possibly other quarterly macroeconomic variables). Hence, information about UK GVA growth at the quarterly frequency can provide information which is useful in interpolating and updating quarterly regional GVA growth. Formally, the model we develop which is consistent with this intuition is a mixed-frequency Vector Autoregressive (MF-VAR). A MF-VAR models a set of time series variables where some of them are observed at a different frequency than others. In our case, the mixed frequency aspect arises since our MF-VAR involves quarterly UK GVA growth and annual GVA growth for the 12 UK regions. In our baseline specifications we augment the MF-VAR with additional quarterly predictors, as these additional predictors are found to help explain intra-year regional growth dynamics. We adopt a state space approach where the unobserved regional quarterly GVA growth rates are treated as latent states. MF-VARs which use state space methods have been popularised in papers such as Eraker, Chiu, Foerster, Kim and Seoane (2015), Schorfheide and Song (2015), Mandalinci (2015) and Brave, Butters and Justiniano (2016).[5] The basic idea underlying this approach is to construct a VAR at the higher (in our case, quarterly) frequency and then treat the unobserved observations for the low (in our case, annual) frequency variables as states in a state space model. Bayesian Markov Chain Monte Carlo (MCMC) algorithms which combine Bayesian state space methods with Bayesian VAR methods can be used to estimate the MF-VAR.

Our empirical problem differs from the ones addressed in the papers cited earlier due to our having many more low than high frequency variables and a smaller number of observations. That is, we have 12 annual frequency variables and only one (or a few) quarterly variables. In contrast, Schorfheide and Song (2015) in their application have 3 quarterly variables and 8 monthly ones. Use of annual low frequency data limits the number of observations we have. Thus, we have many more state equations to estimate and fewer observations with which to do so. To overcome these problems, we extend standard MF-VAR methods in two ways.

First, we use the hierarchical Dirichlet-Laplace prior of Bhattacharya, Pati, Pillai and Dunson (2015) to ensure optimal shrinkage and, thus, parsimony in our MF-VAR. Dirichlet-Laplace priors are a popular machine learning method for Big Data problems, that let the data decide what restrictions to impose. The existing literature which uses this hierarchical prior mostly focuses on single-equation, homoscedastic models. A recent exception to this is Kastner and Huber (2017) who use Dirichlet-Laplace shrinkage in a large VAR with stochastic volatility. We extend these methods to the MF-VAR with stochastic volatility (MF-VAR-SV) and find they are an effective method for ensuring parsimony in our model.

Second, we exploit the fact that UK GVA is the sum of regional GVA. We do this using a method proposed by Doran (1992) for restricting states in a state space model. We find that this, too, helps improve estimation precision; and of course the restriction ensures that our new quarterly regional data are consistent with the observed quarterly UK totals.

The plan of the remainder of this paper is as follows. Our econometric methods are described in Section 2. In Section 3, we present our new quarterly regional estimates and summarise their statistical features. Then in Section 4 we provide three applications of our data, designed to illustrate their utility to economists. These involve firstly looking at business cycle dynamics, where we identify how several regional contractions would be missed without access to our new higher-frequency data.

[5]Ghysels (2016) offers a detailed discussion of the relationship between the state space approach and other mixed frequency methods. Koop, McIntyre and Mitchell (2018) use one of these other approaches, the stacked VAR approach, in a UK regional nowcasting exercise. The stacked VAR approach does not allow for the calculation of smoothed historical quarterly estimates of regional GVA growth which is a key aspect of the present paper.

We also use our new data to compare the high-frequency time-profiles of recessions and recovery in the regions with the four main recessions the UK, as a whole, has experienced since 1970. Secondly, we use connectedness measures developed in Diebold and Yilmaz (2014) to investigate the dynamic connections between the UK regions at the quarterly frequency, finding regions' growth dynamics are largely idiosyncratic in the quarter immediately after a shock but become increasingly common five years later. Third, we show how we can update and then evaluate our regional data in real-time to provide 'nowcasts' of regional growth on an ongoing basis. These up-to-date estimates, alongside updated historical estimates, will be published online each quarter (at `www.escoe.ac.uk/regionalnowcasting`), on receipt of the latest UK data. Section 5 concludes. Appendices contain supplementary material about the data, econometric methods and empirical results.

2 Econometric Methods

2.1 The Model and the Cross-sectional Restriction

In this section, we describe the form of the econometric model that we use to produce the new regional estimates and explain its properties. Complete details of our econometric methods are given in the Technical Appendix.

We use the following notational conventions:

- $t = 1, .., T$ runs at the *quarterly* frequency.
- $r = 1, .., R$ denotes the R regions in the UK.
- Y_t^{UK} is GVA for the UK in quarter t.
- $y_t^{UK} = log(Y_t^{UK}) - log(Y_{t-1}^{UK})$ is the quarterly change in GVA in the UK.
- Y_t^r is GVA for region r in quarter t. It is never observed.
- $Y_t^{r,A} = Y_t^r + Y_{t-1}^r + Y_{t-2}^r + Y_{t-3}^r$ is annual GVA for region r. It is observed in quarter 4 of each year, but not in other quarters.
- $y_t^{r,A} = log(Y_t^{r,A}) - log(Y_{t-4}^{r,A})$ is annual GVA growth in region r. It is observed, but only in quarter 4 of each year. $y_t^A = \left(y_t^{1,A}, .., y_t^{R,A}\right)'$ is the vector of annual GVA growth rates for the R regions.
- $y_t^r = log(Y_t^r) - log(Y_{t-1}^r)$ is the quarterly change in GVA in region r. It is never observed. $y_t^Q = \left(y_t^1, .., y_t^R\right)'$ is the vector of quarterly GVA growth rates for the R regions.

Let $y_t = \left(y_t^{UK}, y_t^{Q\prime}\right)'$ be a vector of $n = R + 1$ variables modelled using a VAR:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + u_t \tag{1}$$

where u_t is i.i.d. $N(0, \Sigma_t)$.

We emphasise that, except for y_t^{UK}, the elements of y_t are not observed and (1) will end up being interpreted as state equations in a state space model.[6] What we do observe (every fourth quarter, ignoring publication lags for now) is the annual regional growth rate $y_t^{r,A}$. Note that we are approximating growth rates using log differences. Following Mitchell, Smith, Weale, Wright and

[6]Below we consider augmenting the vector, y_t, with additional observed quarterly data.

Salazar (2005) and Mariano and Murasawa (2010), the following approximate relationship involving annual and quarterly log differences holds:

$$y_t^{r,A} = \frac{1}{4}y_t^r + \frac{1}{2}y_{t-1}^r + \frac{3}{4}y_{t-2}^r + y_{t-3}^r + \frac{3}{4}y_{t-4}^r + \frac{1}{2}y_{t-5}^r + \frac{1}{4}y_{t-6}^r \tag{2}$$

We can define a matrix, Λ^A, which imposes the intertemporal restriction in (2). We can then write an equation which links what we actually observe of the regional data to the unobserved regional quarterly GVA growth rates which we seek to estimate as

$$y_t^A = M_t^A \Lambda^A z_t \tag{3}$$

where $z_t = \left(y_t', .., y_{t-6}'\right)'$. The role of M_t^A in (3) is explained if we remember that we only observe y_t^A once a year. Thus we define $M_t^A = 1$ for the fourth quarter and M_t^A to be an empty matrix (i.e. of dimension zero) in the first three quarters of each year. We can also use M_t^A to allow for delays in the release of the data, important in practice when nowcasting and forecasting in real-time given the "ragged-edge" or unbalanced nature of the dataset.

The preceding relationships were for regional GVA growth. For the UK they are simpler, since we observe the UK GVA growth every quarter. Hence, we only need a restriction matrix, Λ^{UK}, which picks out the time t value of UK GVA growth from y_t. If there are delays in the release of the data we can construct an M_t^{UK} matrix in a similar fashion as M_t^A. In this case, we simply have $M_t^{UK} = 1$ except for the most recent observations which have not been released yet. With these definitions, we can write

$$y_t^{UK} = M_t^{UK} \Lambda^{UK} y_t. \tag{4}$$

The structure described so far is the same as in Schorfheide and Song (2015). It involves a state space model involving the state equations, given in (1), and measurement equations, given in (3) and (4). We want to add to this the cross-sectional restriction that UK GVA is the sum of GVA across the R regions. For log-differenced data, using derivations as in Mitchell et al. (2005), it can be shown that the following approximate relationship holds[7]

$$y_t^{UK} \approx \frac{1}{R}\sum_{r=1}^{R} y_t^r. \tag{5}$$

We impose this restriction using a method developed in Doran (1992). This involves adding (5) as an additional measurement equation to the state space model.[8] The Technical Appendix provides complete details. We note that, since this relationship is an approximate one, an error is added to (5). An additional reason for this relationship to be an approximate one is that the output from the UK continental shelf (UKCS) is not included in the regional outputs, y_t^Q, given its idiosyncratic time-series properties, but is included in the UK figure, y_t^{UK}. Note that it is not possible to remove UKCS activity from the overall estimates of UK quarterly GVA.[9] The UKCS reflects oil and gas

[7]Note that, if we were to use regional growth rates, then the UK total would be a weighted average of regional growth rates. But, when using log differences which are only an approximation to growth rates, the simple average can be shown to apply.

[8]Our state-space approach to modelling and, in effect, interpolating quarterly regional estimates given both the temporal, (2), and cross-sectional, (5), constraints can be related to an earlier approach (e.g. see Di Fonzo, 1990) where typically, to facilitate least-squares estimation, restrictions are imposed on (1) that rule out dynamic interactions.

[9]While some sectoral detail for GVA is available for the UK as a whole on a more timely basis, not all Oil and Gas related activity in the UK 'Mining & quarrying including oil and gas extraction' sector is activity which takes place in the UKCS. Some of this activity relates to onshore activity in support of activity in the UKCS. Similarly, not all of the activity in this sector relates to oil and gas extraction. It would therefore not be appropriate to treat the 'Mining & quarrying including oil and gas extraction' sector as synonymous with the UKCS activity series.

output from the North Sea. Since both the quantity of oil and gas produced and their price have fluctuated greatly over time it is a very volatile series, with time series properties which are very different from other regions of the UK. Accordingly we exclude it from our VAR.

Thus far, we have not defined Σ_t. In most empirical macroeconomic applications, there is evidence of changes in volatility (although the mixed frequency VAR literature has mostly ignored this issue and works with homoscedastic models). In this paper we adopt a popular multivariate stochastic volatility specification (see Cogley and Sargent, 2005 and Carriero, Clark and Marcellino, 2016). This decomposes the error covariance matrix as:

$$\Sigma_t^{-1} = \mathbf{L}^{'}\mathbf{D}_t^{-1}\mathbf{L}, \tag{6}$$

where $\mathbf{L}$ is $n \times n$ lower triangular matrix with ones of the diagonal

$$\mathbf{L} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{1,1} & 1 & & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{n,1} & & a_{n,n-1} & 1 \end{bmatrix}, \tag{7}$$

and we define $\mathbf{a} = (a_{1,1}, a_{2,1}, \ldots, a_{n,1}, a_{2,1}, \ldots, a_{n,n-1})'$ as an $m \times 1$ vector. $\mathbf{D}_t = \text{diag}(\exp(h_{1,t}), \ldots, \exp(h_{n,t})]'$ and the log-volatilities $\mathbf{h}_t = (h_{1,t}, \ldots, h_{n,t})'$ evolve according to a random walk:

$$\mathbf{h}_t = \mathbf{h}_{t-1} + \nu_t, \nu_t \sim N(0, \Sigma_h), \tag{8}$$

where $\Sigma_h = \text{diag}(\omega_{h_1}^2, \ldots, \omega_{h_n}^2)$.

We label our MF-VAR with this multivariate stochastic volatility specification as the MF-VAR-SV. Our complete specification includes the cross-sectional restriction and this stochastic volatility specification. The insight that allows for Bayesian estimation and forecasting using this model is that, as shown in the Technical Appendix, we have just specified a state space model and standard methods for posterior simulation and forecasting in state space models exist (see, e.g., Koop and Korobilis, 2009, or Chan, 2017).

2.2 Dirichlet-Laplace Hierarchical Prior for Optimal Shrinkage

The MF-VAR defined in the previous sub-section is undoubtedly over-parameterised and is not parsimonious. The VAR embedded in the MF-VAR is quite large (involving, even before we include any additional macroeconomic indicators, $n = R + 1 = 13$ dependent variables); and our frequency mis-match means that we have 12 latent state variables to be estimated. In addition we have the multivariate stochastic volatility process to estimate. In the Bayesian VAR literature, prior shrinkage is used to avoid such over-parameterisation concerns in high-dimensional models.

Traditionally, subjective Bayesian priors have been used, although these are carefully chosen to reflect empirical patterns which often exist with macroeconomic data. The most popular of these is the Minnesota prior (see Doan, Litterman, and Sims, 1984, and Litterman, 1986) which reflects the empirical wisdom of the authors and has been found to work well with many data sets (see Koop and Korobilis, 2009 and Dieppe, Legrand and van Roye, 2016, for a range of related priors in this class). However, arising from the machine learning literature, there has been a growth of interest in hierarchical priors which automatically induce shrinkage in high-dimensional parameter spaces and require fewer subjective prior choices. In the Bayesian VAR literature, George, Sun and Ni (2008), Koop (2013) Korobilis (2013) and Gefang (2014), were early contributions which showed how various machine learning methods involving hierarchical priors could successfully be used with large VARs.

Recent developments in the statistical theory (see, Bhattacharya, Pati, Pillai and Dunson, 2015) show that one particular method induces shrinkage which is, in a theoretical sense, optimal. This is the Dirichlet-Laplace hierarchical prior. Kastner and Huber (2017) is a recent paper which uses Dirichlet-Laplace shrinkage in a large VAR. To our knowledge, Dirichlet-Laplace methods have not been used in mixed frequency models. Thus, our wish to use such methods with the MF-VAR defined in the preceding sub-section.

In the Technical Appendix, we provide a formal definition of the Dirichlet-Laplace prior and describe how Bayesian inference proceeds when using it with our MF-VAR. Here we outline the general idea of what these hierarchical shrinkage methods do in the context of a VAR coefficient, β_j. A conventional Bayesian prior might take the form:

$$\beta_j \sim N(0, V_j). \tag{9}$$

Such a prior would shrink the estimate of β_j towards the prior mean of zero relative to, e.g., a maximum likelihood estimate (MLE). The prior variance, V_j, determines the degree of shrinkage. Large values of V imply very little shrinkage is done and the Bayesian estimate is similar to the MLE. However, if V_j is close to zero, then the coefficient is shrunk towards zero. In the limit, the coefficient is set to zero and the j^{th} explanatory variable is removed from the model.

What the Bayesian variable selection literature does is treat V_j as an unknown parameter and estimates it. Thus the prior for the VAR coefficient is hierarchical: it is expressed in terms of an unknown parameter which in turn requires its own prior. The estimation algorithm automatically decides whether V_j should be near zero or not. Many different specifications have been proposed for V_j. For instance, the popular Bayesian Lasso is one. In this paper, we use the Dirichlet-Laplace prior since it can be shown to lead to a posterior which contracts to the true value at a rate which is better than other alternatives such as the Bayesian Lasso. It is an example of a global-local shrinkage prior since it involves V_j being composed of some terms which are local (i.e. specific to the j^{th} coefficient) and a term which is global (i.e. common to all VAR coefficients in an equation). Allowing for separate estimation of local and global shrinkage has been found to be useful in obtaining an appropriate degree of parsimony in high-dimensional models.

One point worth stressing is that, in addition to doing Dirichlet-Laplace shrinkage on the MF-VAR coefficients, we also shrink the coefficients in $\mathbf{a}$ from (7). These control the error covariances and, empirically, we have found that allowing for prior shrinkage on this high-dimensional vector of parameters can be helpful in inducing parsimony.

3 Empirical Results: Quarterly Regional Growth Estimates

3.1 Annual Regional and Quarterly Macroeconomic Data

The ONS have published annual nominal GDP or GVA estimates (via the income approach) for the regions of the UK since the late 1960s, although there have been changes to accounting standards and to the geographic definitions of the regions since then. This means that, after some basic data analysis and geographic reconciliation as described in the Data Appendix, we have an annual data set of nominal GVA, for the $R = 12$ currently defined NUTS 1 regions, from 1966. We also have quarterly UK GVA data from 1966.

Aware of the potential importance of modelling real-time data given data revisions, we have constructed two versions of the nominal GVA data set: a latest vintage[10] and a real-time one. When producing historical estimates of quarterly regional growth rates, we use the latest vintage. We also

[10] At the time of writing the latest vintage is December 2017.

use the latest vintage data in our discussion of recession profiles and regional connectedness, on the assumption that they offer the ONS's best current assessment of historical regional economic activity.

The real-time data set is constructed from hard and archived electronic back copies of the ONS's *Regional Trends* publications, a database of first-release estimates of nominal GVA for these 12 regions. This first-release data is used in our nowcasting and forecasting exercise as reflecting information the forecaster would have had available at the time the forecast was being made. Clements and Galvao (2013) have advocated a similar use of 'lightly revised' data instead of using data from the latest-available (real-time) vintage.

We also construct an annual real GVA data set for the UK regions which goes back to 1966, but for this we only have a final vintage data set which comprises data from two sources. The first is data published by ONS for the first time in December 2017, which comprised a 'balanced' estimate of regional GVA (referred to GVA(B) by ONS) covering the period 1998 to 2016. These GVA(B) data, which reconcile the income and production based estimates of GVA (see Fenton (2018) for details), are classed by the ONS as '*experimental*' rather than, like the nominal data, official *National Statistics*. The second is obtained by deflating the available nominal regional GVA data using the UK deflator in the absence of real data for the regions covering this earlier period. Thus, the real regional data in the first part of our sample will not fully reflect cross-regional variation in prices and will not be of as high quality as our nominal GVA data.

Using these annual observations for either nominal or real regional GVA, we use the MF-VAR-SV model, (1), to produce quarterly regional growth rate estimates for these 12 regions of the UK; this implies $\left(y_t^{UK}, y_t^{Q\prime}\right)'$ is a 13-dimensional vector. Importantly, this means that as well as region-specific and cross-region information, as captured by y_t^Q, observed quarterly information from UK growth, y_t^{UK}, is used to help explain within-year regional growth dynamics and thereby provide quarterly interpolated estimates y_t^Q. These quarterly GDP data, for the UK as a whole, are published with a much shorter lag than the regional data. But as a range of observed quarterly macroeconomic series, in addition to y_t^{UK}, might be expected to provide helpful indications of quarterly regional growth we follow the recent literature (e.g. Schorfheide and Song (2015); Brave, Butters and Justiniano (2016)) in considering additional high-frequency macroeconomic indicators in our MF-VAR. As the UK is a small open economy, in the tradition of Sims (1992), we augment the VAR with four quarterly macroeconomic variables for the UK: inflation, interest rates (the Bank Rate), the exchange rate and the oil price.[11] Complete details about our data and the way they are transformed are given in the Data Appendix.

3.2 Model Choice

Our empirical results are based on an MF-VAR, (1), that is 17-dimensional. That is, the vector of dependent variables is $y_t = \left(y_t^{UK}, y_t^{Q\prime}, x_t^{UK\prime}\right)'$, where x_t^{UK} contains the four additional quarterly macroeconomic variables. Complete details of how we carry out Bayesian estimation and forecasting with these models in given in the Technical Appendix.

In the Empirical Appendix we provide justification for choosing this specification based on comparison of the marginal likelihoods. These provide strong evidence for the importance of allowing for stochastic volatility in our data sets. Furthermore, there is evidence that including the additional quarterly variables (instead of working with a 13-dimensional model involving only GVA data) is

[11]The choice of these variables is motivated partly by our wish to produce historical estimates of regional GVA growth and, thus, wishing to use variables for which data goes back to 1966. Other potentially interesting predictors (e.g. those based on surveys such as the Purchasing Managers' Index) do not go back this far.

empirically warranted. Similarly, our preferred lag length ($p = 4$) is supported by marginal likelihoods. However, it is worth stressing that use of the Dirichlet-Laplace shrinkage prior should remove extraneous coefficients, so the cost of using a more parameter rich model than is necessary is low.

We also experimented with other priors such as the Minnesota prior and the spatial prior of LeSage and Krivelyova (1999), but found the Dirichlet-Laplace to produce a higher marginal likelihood. Another advantage of the Dirichlet-Laplace is that prior hyperparameter choice is automatic and does not require a great deal of subjective prior input from the researcher. See the Technical Appendix for further details.

3.3 Historical Estimates of Quarterly Regional Growth

We estimate our MF-VAR-SV models on the final vintage data to produce historical quarterly estimates of both nominal and real regional growth. Downloadable files containing the full set of historical estimates are made available online. We remind the reader that we plan on using our model to update these estimates in real-time and these will also be made available online - at `www.escoe.ac.uk/regionalnowcasting`.

Figure 1 presents the nominal and real estimates alongside the UK growth rate. To aid in comparability with the published annual regional data, our quarterly estimates are annualised (i.e. we take our quarterly regional GVA estimates and construct an annual change using (2)).

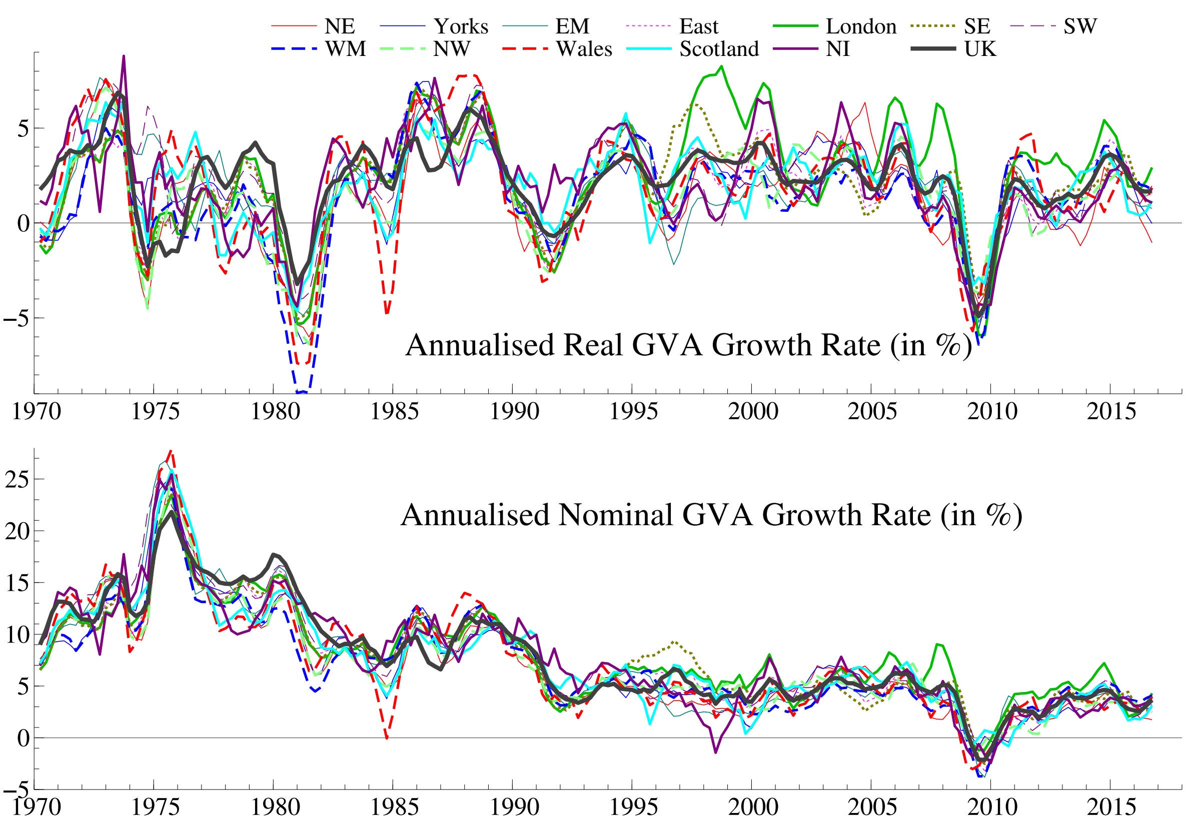


Figure 1: Historical Estimates of Regional GVA Growth

Section 4 below illustrates how use of our new data can enrich our understanding of the UK economy. Before this we draw out four statistical features of the new data.

First, as Figure 1 shows, while the UK growth rates tend to lie in the middle of the more volatile regional growth rates and, in general, regional and UK growth rates tend to move together, this is not always the case. On occasion the UK growth figure differs from the (cross-regional) average of our quarterly estimates. This is possible because the cross-sectional restriction in (5) is approximate since the UKCS is not included as a region, but UKCS output is included in the UK figure. For this reason, as the share of UKCS in UK GVA temporarily rose to around 6% in the early 1980s with the rise in the oil price, we see UK growth exceeding that of all regions. In general, however, our econometric techniques are estimating the cross-sectional restriction to hold fairly precisely, particularly in the latter half of the sample. This can be seen in Figure 2 which plots the estimate of the error in the measurement equation, (2), along with a credible interval. This shows how the information in UK GVA growth, via the cross-sectional restriction, is pulling our regional estimates away from those that would be produced by univariate benchmarks. That is, methods in the tradition of Chow and Lin (1971) interpolate quarterly estimates from the observed annual totals but do not impose the cross-sectional constraint or indeed exploit the cross-region and cross-variable linkages that our VAR in $y_t = \left(y_t^{UK}, y_t^{Q\prime}, x_t^{UK}\right)'$ permits.

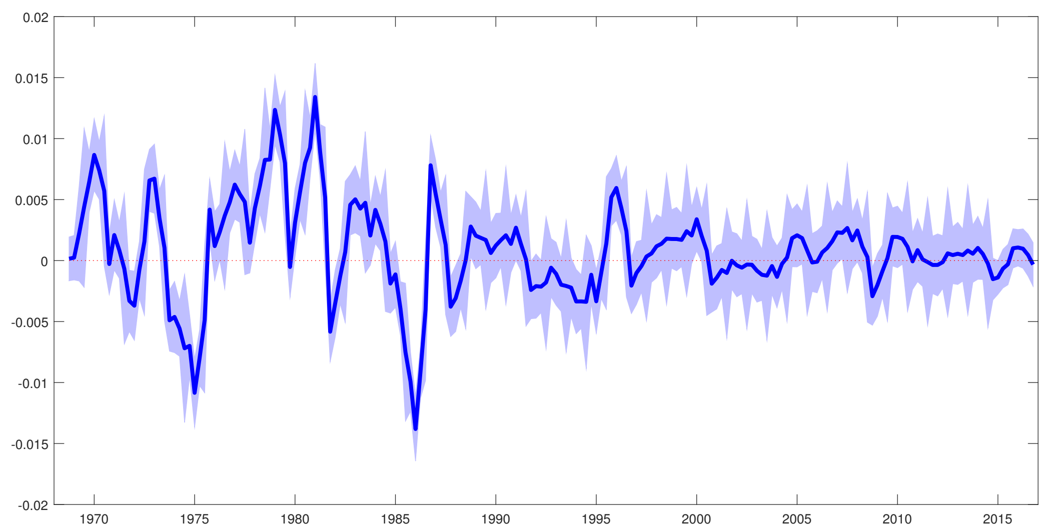


Figure 2: Errors in Cross-sectional Restriction (68 percent credible interval is shaded)

Secondly, inspection of the 68 percent credible intervals around our regional nominal and real GVA growth estimates (see Empirical Appendix) shows that our regional estimates are quite precise. Since we plot annualised quarterly estimates once a year our estimates, which impose the intertemporal restriction in (2), equal the actual observed annual regional growth rate. This accounts for why the credible intervals go to zero once each year.

Third, as a further robustness check, we repeated our analysis using an alternative prior. This was the spatial prior of LeSage and Krivelyova (1999) which reflects the spatial contiguity of neighbouring regions. The estimates of regional quarterly GVA growth produced by this prior were very similar to those produced using the Dirichlet-Laplace prior. Since the Dirichlet-Laplace prior produces higher marginal likelihoods the results in the body of the paper use this prior. Results using the spatial prior are included in the Empirical Appendix along with complete details of the spatial prior.

Fourth, as one check on the accuracy, or certainly the credibility, of our interpolated quarterly estimates - and ahead of the forecasting exercise below that provides an out-of-sample test - we exploit the fact that, for Scotland, we do now observe quarterly real GVA estimates from 1997 Q1. Although we should stress that the ONS and Scottish Government estimates for GVA in Scotland are expected to differ, due to methodological differences. In particular, the ONS when measuring real GVA for the regions apply top down (sectoral) deflators to the regions, whereas the Scottish government go the other way and build up their deflators for Scotland as the ONS does for the UK as a whole. Nevertheless, it would be worrying if our estimates bore no relationship to those from the Scottish Government, so we do compare our quarterly estimates with theirs. Reassuringly, as Figure C.5 in the Empirical Appendix shows, our estimates do track those from the Scottish Government, with a correlation coefficient (RMSE) of 0.77 (0.012) against the Scottish data[12].

4 Applications of the new data

In this section we illustrate three uses of the new quarterly regional data. First, we compare the high-frequency time-profiles of recession and recovery in the regions with the four main recessions the UK, as a whole, has experienced since 1970. Second, we analyse the dynamic connections between the regions of the UK. Third, we show how we can update and then evaluate our regional data in real-time to provide nowcasts of regional growth on an ongoing basis.

4.1 Recessions Profiles Within the UK

Our high frequency regional data help us gain a more complete picture of the nature of UK recessions since 1970. As seen in Figure 1 above, UK downturns do tend to be accompanied, as we should expect, with downturns at the regional level. But the regional cycles are more volatile and often de-couple from the path of the UK as a whole.

To draw out further common and contrasting features of these regional business cycles, we apply the nonparametric business cycle dating algorithm of Harding and Pagan (2002) to our real regional and UK data (having transformed them back into log-levels) to identify the turning points that separate business cycle expansions from contractions. We use the median historical estimates of real GVA since recessions are typically defined in terms of real quantities.[13] This algorithm identifies four

[12]This correlation coefficient is 0.94 when comparing our estimates to the Scottish GDP series produced prior to a change in the calculation of activity in the Construction sector which the Scottish Government brought in earlier in 2018. This change in methodology reflects a further difference in methodology with that used by the ONS in producing its regional growth estimates. It is therefore no surprise that this slightly weakens the correlation between our estimates, using a model based on ONS data, and the data now produced by the Scottish Government. More information on this change in methodology can be found on p7 of this report: `https://www.gov.scot/Resource/0053/00539194.pdf`

[13]In principle, we could acknowledge the estimation uncertainty in these real GVA estimates when dating the contractions and expansions by applying the dating algorithm to each draw from our MCMC algorithm. We explore estimation precision further below, in the context of measuring the dynamic connections between the regions. But recall that Figures C1 to C4, in the Empirical Appendix, found the credible intervals around the central regional growth estimates to be quite precise. While there are differences, a qualitatively similar picture to that found below also emerges when we analyse the nominal rather than real GVA data; in particular, business cycle phases still exhibit considerable variation at the regional level relative to the UK aggregate. This mitigates a concern that, prior to 1998, our use of a UK deflator, in the absence of regional deflators, maybe exaggerating regional disparities in real GVA to the extent that removing common (UK-wide) inflation from the nominal data leaves residual region-specific inflationary components in our real GVA estimates. Further reassurance that our results are not an artefact of the absence of regional inflation data is evidence from a 2017 feasibility study, at the ONS, into producing regional inflation estimates, see `https://www.ons.gov.uk/economy/inflationandpriceindices/methodologies/feasibilitystudyintoproducingcpihconsistentinflationratesforukregions`), that the basic patterns in regional inflation, especially when housing costs are removed, are similar to those of UK inflation.

main recessions for the UK as a whole. These start in 1973Q3 (continuing in 1974), 1979Q3, 1990Q3 and 2008Q2.[14]

Figure 3 plots the quarter in which each region, as well as the UK as a whole, entered and exited recession. This figure shows considerable variation as to the frequency and timing of recessions across regions. This variation is most marked during the 1970s and the period since the global financial crisis. The lacklustre recovery since 2008, and real-time talk of double and indeed triple dip recessions (e.g. see `https://www.bbc.com/news/business-22277955`) although subsequently revised away at the national level, is still evident when looking at the regional cycles since 2008. While the UK as a whole has been in an expansionary phase since 2009Q3, all regions except London and the South East have experienced at least one recession since then. Many of these regional contractions were short-lived and intra-year, and would be missed without access to our new higher-frequency data. But perhaps the Brexit heckler, from Newcastle in the North East, was well aware of them.

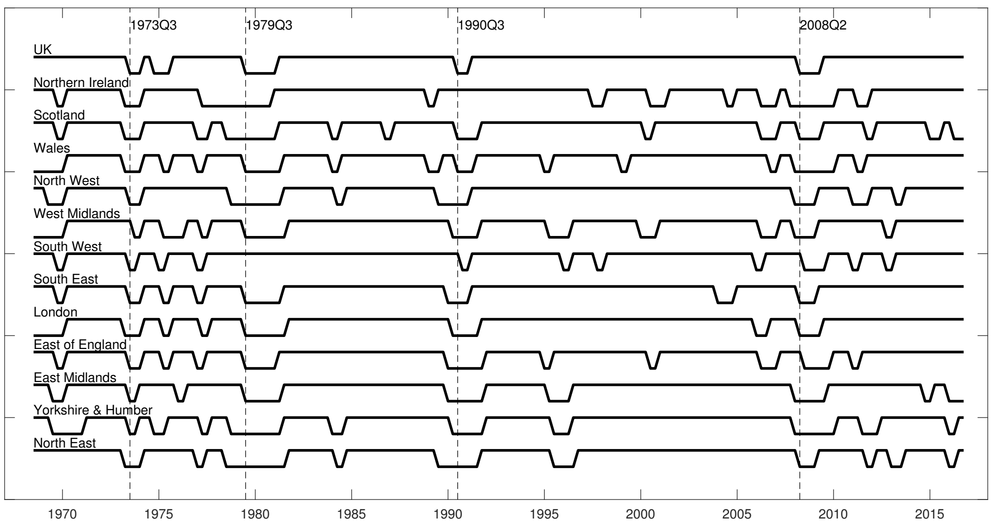


Figure 3: Start and End Dates of Regional and UK Recessions Using Quarterly Real GVA

Similarly, the so-called Great Moderation period, after the UK recession of 1990Q3, while associated with 68 expansionary quarters for the UK as a whole (from 1991Q2 to 2008Q1) is also characterised by 24 regional recessions, four of which were in Northern Ireland alone. Again this cross-regional variation is lost if we focus on extant annual regional data.

Table 1 indicates the mean duration and amplitude of these business cycle phases from 1970, confirming the impression from Figure 1 that the UK aggregate smoothes out the many regional idiosyncrasies, i.e. regional business cycle 'ups and downs'. Table 1 shows that while the UK as a whole spent, on average, 31 quarters in expansionary phases of the business cycle, 8 of the 12 regions (North East, Yorkshire and the Humber, East, South West, West Midlands, Wales, Scotland and Northern Ireland) spent less than half this time in an expansion. The amplitude of these expansions

[14] These dates mostly accord with the views of others; e.g. The Conference Board recession dates for the UK are June 1973, November 1979, May 1990, May 2008 and August 2010. The Harding and Pagan dating algorithm seeks to formalise aspects of how the NBER date business cycles in the US, and has been found to match their turning points better than commonly used rules of thumb that characterise a recession as, for example, at least two consecutive quarters of negative growth. We note that we would arrive at similar recession dates for the UK as a whole if we did use this two quarters of negative growth rule.

Table 1: Properties of Regional Contractions and Expansions

	Durations (quarters)		Amplitude (quarters)		Concordance
	Contractions	Expansions	Contractions	Expansions	
North East	4.60	14.11	-0.04	0.11	82%
Yorkshire and The Humber	4.91	13.40	-0.04	0.11	81%
East Midlands	4.63	18.63	-0.04	0.15	85%
East of England	3.64	12.70	-0.03	0.11	88%
London	4.43	18.00	-0.04	0.19	90%
South East	3.75	18.29	-0.04	0.16	93%
South West	2.27	14.90	-0.03	0.13	86%
West Midlands	4.40	12.80	-0.04	0.10	81%
North West	4.75	20.00	-0.05	0.15	87%
Wales	3.50	10.33	-0.05	0.11	84%
Scotland	3.75	11.75	-0.03	0.11	83%
Northern Ireland	4.90	13.33	-0.03	0.14	78%
UK	4.40	30.50	-0.04	0.23	100%

is also seen to vary considerably across regions with London, like the UK aggregate, growing by around 20% points in an average expansion; with the other regions often growing much more modestly.

This cross-region heterogeneity is also reflected when we follow Harding and Pagan (2002) and measure the degree of co-movement between the regional cycles and that of the UK aggregate using Harding and Pagan's measure of concordance. This measure quantifies the fraction of time both series are simultaneously in the same contractionary or expansionary state. This reveals a north-south divide in England with London, the South East and the East having concordance estimates of 90%, 93% and 88% respectively; with the North East, Yorkshire and the Humber and the North West having lower estimates of 82%, 81% and 87%, respectively. The East and West Midlands are in the middle, as their names suggest, with estimates of 85% and 81%, respectively. Of the devolved nations, Northern Ireland again stands out as the most idiosyncratic with the lowest concordance estimate of 78%; and Scotland and Wales have estimates of 83% and 84%, respectively, placing them as more similar to the northern than the southern regions of England.

To illustrate further how our new quarterly data are helpful in analysing and understanding the transmission of shocks and business cycle dynamics, Figure 4 presents regional recession profiles for the four main UK recessions since 1970. The figure shows that while the 2008 recession was the deepest and longest lasting at the UK level, it was the 1979 recession which was the deepest for many regions, with the West Midlands, Scotland, North West, Yorkshire and the Humber and Northern Ireland particularly hard hit. This is consistent with macroeconomic analysis showing the differential effects of the 1970s oil price shocks, particularly on the UK manufacturing and tradeable goods sectors (e.g. see Bruno and Sachs, 1982). Recall from Section 3.3, and Figure 2, that the UK as a whole recovered from the 1979 recession faster than the twelve regions due to the boost from the oil and gas sector.

Another interesting feature of Figure 4, bearing in mind the widely held belief that economic growth in London dominates that of the other regions of the UK, is that London's strong bounceback from the 2008 recession is not observed in previous recoveries where London recovers in-line with the other regions of the UK. Our new data, as they let us better appreciate regions' intra-year dynamics, also emphasise the stop-start nature of the economic recoveries of many of the regions, in particular Northern Ireland, after the 1979 and 2008 recessions.

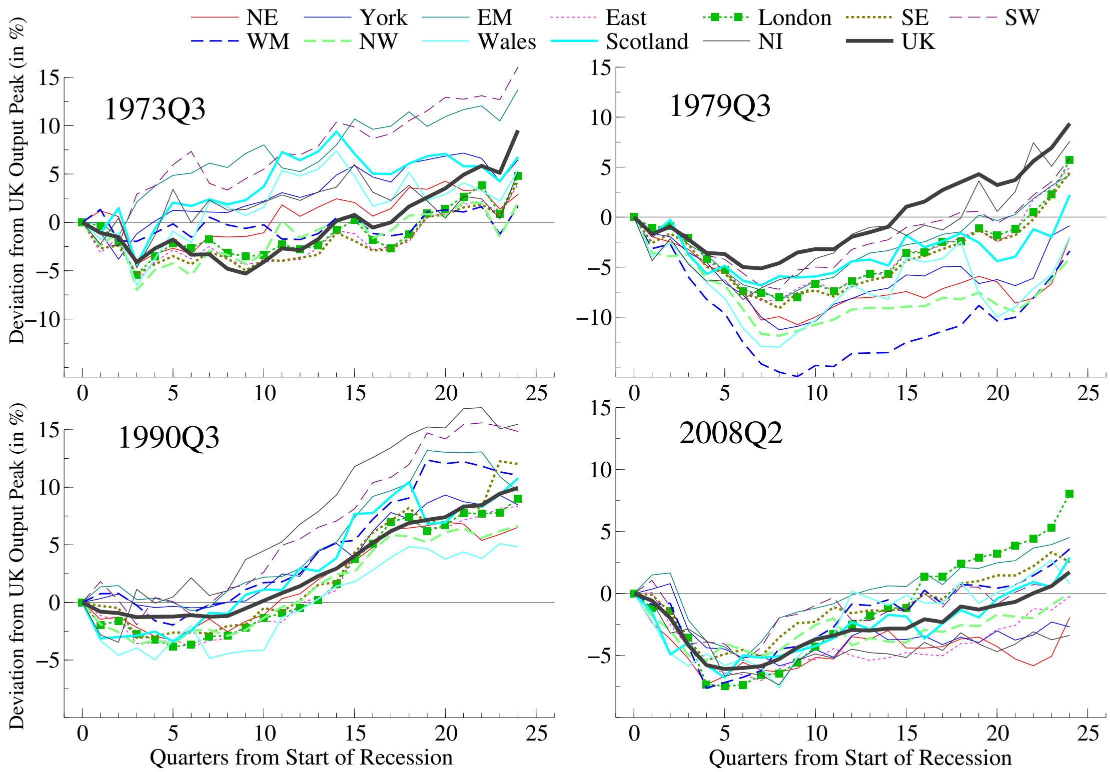


Figure 4: The regional profiles of four UK recessions

4.2 The Connectedness of the UK Regions

4.2.1 Measuring Connectedness

We complement our comparison of historical regional and UK business cycles by now presenting evidence on the dynamic connections between the UK regions. We use connectedness measures developed in Diebold and Yilmaz (2014). Due to the presence of multivariate stochastic volatility these measures will vary over time, as in Korobilis and Yilmaz (2018).

The connectedness measures are based on a variance decomposition and we use the generalised variance decomposition developed in Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998). These are invariant to the ordering of the variables in the VAR. We use the formula on top of page 20 of Pesaran and Shin (1998) to produce variance decompositions $d_{i,j}^{h}$ for $i, j = 1, .., n$ and $h = 1, .., H$. Each of these is the proportion of the h-step ahead forecast error for variable i which is accounted for by the errors in the equation for variable j.

The variance decompositions involve the parameters of our VAR given in equation (1). To be precise, each draw from the MCMC algorithm provides all the variables and the parameters in (1) and we use these to compute the variance decompositions. This provides us with draws of $d_{i,j}^{h}$ which we then average to produce estimates. Thus, the results in this sub-section reflect the uncertainty present in the quarterly regional growth rates. That is, we are not simply taking the point estimates of regional quarterly GVA growth produced in the preceding section and estimating a VAR using them.

Using these variance decompositions we can define the total directional connectedness from other regions to region i at horizon h as

$$\text{Connectedness } \textbf{from}\text{: } \sum_{j \neq i} d_{i,j}^{h} \tag{10}$$

This is a measure of how information in other regions impacts the forecast error variance of region i (i.e. the summation is over j). This is called a "*connectedness from*" measure.

The total directional connectedness to other regions from region j at horizon h is

$$\text{Connectedness } \textbf{to}\text{: } \sum_{i \neq j} d_{i,j}^{h} \tag{11}$$

This is a measure of how information in region j influences the forecast error variances of other regions (i.e. the summation is over i). This is called a "*connectedness to*" measure.

We emphasise that our connectedness measures are based on a quarterly frequency VAR. Thus, e.g., results for $h = 20$ measure connectedness in terms of the five year ahead forecast error variances. Since the key contribution of this paper is to produce quarterly estimates of regional GVA growth, in this section we focus on the connectedness measures at $h = 1$, although we do present some long run results for $h = 20$. Of course, the $h = 1$ estimates could not be produced using a standard VAR with annual data.

4.2.2 Connectedness Results

Tables 2 and 3 contrast the pattern of connectedness between the UK regions in the short ($h = 1$) and longer run ($h = 20$) using our nominal data.[15] As shown in the Empirical Appendix the pattern of connectedness is similar when we consider the real data, so we do not discuss it separately. We will return to how connectedness may have changed over time, but Tables 2 and 3 provide posterior mean estimates at the end of our sample. In the Empirical Appendix we produce tables with the same format, but for the 16th and 84th percentiles of the posterior distribution. These can be used to gauge estimation precision.

Table 2 shows that in the short-run ($h = 1$) the degree of interconnectedness, although moderately high, is dominated by region-specific effects. This is seen by focusing on the diagonal elements of the tables which reflect the importance of region-specific effects. Across regions, we see that idiosyncratic or region-specific shocks explain around two thirds of short-run regional growth dynamics. The role of common shocks is even more muted for some regions, in particular Yorkshire and the Humber where more than three-quarters of their error variation is explained by shocks specific to that region. This picture of regions reacting idiosyncratically contrasts the earlier findings, using annual data, of Forni and Reichlin (2001) who found 60-75% of the variation in regional growth is explained not by region-specific but a common/UK-wide component.

The *connectedness from* measure varies somewhat across regions. It tends to be highest for regions in the middle or south of the country (i.e. the East of England, East Midlands and the South East have the highest *connectedness from* measures) and (with some exceptions) lower for regions at the periphery (i.e. Scotland, Northern Ireland and Wales have among the lowest total *connectedness from* measures).

The *connectedness to* measures tend to be lower than the connectedness from measures. A notable difference between the *connectedness to* and *connectedness from* results is that for Wales, Scotland and Northern Ireland we see higher numbers than for the other regions.

[15] Note that, because the errors are not orthogonal, sums of forecast error variance contributions do not necessarily sum to one. Following Diebold and Yilmaz (2014) we normalise them so they do sum to one. To be specific, across rows (but not down columns) in the connectedness tables the percentages sum to 100.

Note that these *connectedness to* and *connectedness from* measures sum over all other variables in the VAR model, including UK GVA growth and the additional macroeconomic variables, x_t^{UK}. We can calculate these measures summing only over the other regions i.e. excluding x_t^{UK} and y_t^{UK}. When we do this, we find the previous conclusions to hold, but in a weaker form. The *connectedness to* values for these other variables show the impact of these other indicators on GVA growth in the UK regions. In this regard, the oil price stands out as having a very large impact on all of the regions.

In contrast, Table 3 paints a very different picture and indicates that the inter-connections between regions are much higher at this longer forecast horizon; and the role of the oil price is even larger. Across regions the idiosyncratic or region-specific shocks typically now explain less than one fifth, rather than two thirds, of short-run regional growth dynamic. Thus, we are finding evidence that an appreciable amount of time is required for growth in one region to spill over to another.

Table 2: Connectedness Estimates for 2016Q4, 1 quarter ahead forecast horizon

	UK	CPI	Bank rate	Ex. rate	Oil price	North East	York and H.	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland	**From**
UK	65.9%	0.6%	0.7%	0.4%	0.5%	1.7%	1.2%	5.0%	5.8%	3.4%	4.4%	2.0%	1.4%	1.4%	1.5%	0.9%	3.3%	**34.1%**
CPI	0.9%	71.9%	2.1%	0.9%	0.3%	0.2%	0.3%	5.1%	4.1%	2.1%	0.6%	0.5%	0.5%	0.7%	5.3%	2.1%	2.4%	**28.1%**
Bank rate	1.0%	2.0%	76.3%	0.2%	0.1%	0.4%	0.6%	3.4%	5.4%	2.01%	1.9%	0.6%	0.7%	0.8%	1.3%	2.1%	1.2%	**23.7%**
Ex. rate	0.1%	0.2%	0.0%	70.2%	6.3%	2.6%	2.9%	0.7%	0.7%	1.0%	0.9%	1.9%	1.0%	1.4%	5.3%	2.5%	2.2%	**29.8%**
Oil price	0.0%	0.0%	0.0%	1.7%	68.8%	1.4%	0.7%	1.5%	2.1%	3.0%	1.6%	1.4%	1.4%	6.5%	4.5%	3.7%	1.6%	**31.2%**
North East	0.6%	0.0%	0.1%	3.2%	5.9%	69.7%	0.5%	0.9%	1.3%	1.2%	1.1%	1.2%	0.8%	2.5%	5.7%	2.7%	2.5%	**30.3%**
York and H.	0.4%	0.1%	0.2%	3.7%	3.6%	0.6%	75.8%	0.8%	2.2%	1.6%	1.0%	2.1%	2.0%	1.3%	1.5%	1.9%	1.2%	**24.2%**
E. Midlands	1.5%	1.1%	0.8%	0.9%	5.9%	0.9%	0.7%	57.8%	7.9%	4.8%	2.8%	2.6%	1.4%	3.3%	2.4%	1.9%	3.2%	**42.2%**
E. of England	1.3%	0.6%	0.9%	0.7%	6.1%	1.0%	1.4%	5.3%	60.3%	1.6%	1.4%	1.4%	1.5%	3.4%	6.1%	3.8%	3.3%	**39.8%**
London	0.7%	0.3%	0.3%	0.9%	7.8%	0.8%	1.0%	3.2%	1.8%	69.4%	1.6%	1.4%	2.1%	2.2%	2.0%	2.6%	1.8%	**30.6%**
South East	1.2%	0.1%	0.4%	1.0%	6.0%	1.0%	0.8%	2.4%	2.0%	2.2%	66.3%	1.1%	1.0%	1.8%	1.5%	1.1%	10.2%	**33.8%**
South West	0.6%	0.1%	0.1%	2.0%	5.5%	1.1%	1.7%	2.4%	2.0%	1.9%	1.2%	69.0%	4.2%	3.3%	1.9%	1.1%	1.9%	**31.0%**
W. Midlands	0.4%	0.1%	0.1%	1.1%	5.2%	0.7%	1.5%	1.3%	1.9%	2.5%	1.0%	3.6%	72.6%	1.7%	2.6%	2.2%	1.4%	**27.4%**
North West	0.2%	0.1%	0.1%	0.9%	11.5%	1.4%	0.6%	1.9%	2.5%	1.7%	1.1%	2.0%	1.1%	65.2%	6.2%	2.0%	1.6%	**34.8%**
Wales	0.2%	0.5%	0.1%	2.8%	7.5%	2.5%	0.6%	1.0%	3.6%	1.3%	0.7%	0.9%	1.4%	4.9%	68.2%	1.8%	2.1%	**31.9%**
Scotland	0.1%	0.2%	0.2%	1.7%	7.9%	1.5%	0.9%	1.1%	2.8%	2.0%	0.7%	0.7%	1.5%	2.4%	2.5%	71.7%	2.0%	**28.3%**
N. Ireland	0.4%	0.2%	0.1%	1.4%	3.8%	1.2%	0.5%	1.7%	2.4%	1.4%	5.1%	1.1%	0.8%	1.6%	2.5%	1.9%	73.9%	**26.1%**
To	**9.7%**	**6.4%**	**6.3%**	**23.5%**	**83.9%**	**18.9%**	**16.0%**	**37.9%**	**48.5%**	**33.7%**	**27.0%**	**24.5%**	**23.0%**	**39.4%**	**52.9%**	**34.3%**	**41.7%**	31.0%

Table 3: Connectedness Estimates for 2016Q4, 20 quarter ahead forecast horizon

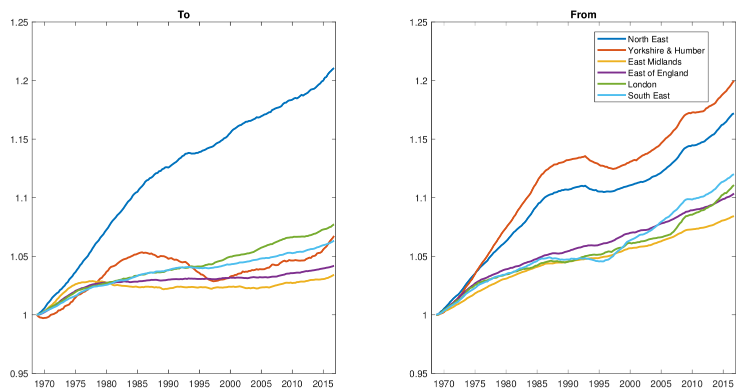
	UK	CPI	Bank rate	Ex. rate	Oil Price	North East	York. and H.	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland	**From**
UK	18.9%	3.8%	2.6%	3.4%	8.2%	3.2%	2.8%	6.0%	6.9%	5.4%	4.6%	4.2%	3.9%	6.3%	7.5%	5.3%	6.9%	**81.1%**
CPI	8.5%	22.8%	6.8%	4.6%	8.4%	2.1%	2.0%	6.3%	6.1%	4.0%	2.9%	3.0%	2.5%	4.4%	6.7%	3.8%	5.0%	**77.2%**
Bank rate	10.3%	6.6%	22.6%	5.0%	7.6%	2.2%	2.2%	5.3%	6.4%	4.0%	3.6%	3.1%	2.9%	4.4%	5.3%	3.8%	4.6%	**77.4%**
Ex. rate	3.6%	2.6%	1.9%	21.4%	9.8%	3.8%	3.4%	4.0%	5.1%	4.8%	3.7%	4.0%	3.9%	6.5%	8.9%	6.0%	6.6%	**78.6%**
Oil price	3.4%	1.4%	1.4%	3.3%	18.4%	4.2%	3.3%	4.5%	6.2%	6.3%	4.5%	4.4%	4.9%	8.8%	9.3%	7.1%	8.8%	**81.7%**
North East	4.2%	1.0%	0.9%	3.2%	9.4%	10.7%	3.6%	4.9%	6.6%	6.2%	4.7%	4.9%	5.0%	8.6%	10.0%	7.6%	8.4%	**89.3%**
York. and H.	4.1%	1.0%	0.9%	3.3%	9.2%	4.0%	10.2%	5.0%	6.8%	6.2%	4.9%	5.0%	5.3%	8.5%	9.7%	7.6%	8.5%	**89.8%**
E. Midlands	4.2%	1.2%	1.1%	3.0%	9.5%	3.9%	3.4%	11.4%	7.3%	6.5%	4.9%	5.1%	5.0%	8.4%	9.5%	7.2%	8.4%	**88.6%**
E. of England	4.2%	1.0%	1.0%	2.8%	9.3%	3.8%	3.3%	5.4%	15.4%	6.0%	4.8%	4.7%	4.9%	8.2%	9.6%	7.3%	8.2%	**84.6%**
London	4.0%	0.9%	0.9%	2.8%	9.6%	3.7%	3.4%	5.1%	6.5%	16.1%	4.8%	4.7%	5.1%	8.1%	9.0%	7.2%	8.0%	**83.9%**
South East	4.2%	0.9%	1.0%	2.9%	9.4%	3.9%	3.4%	5.0%	6.8%	6.3%	12.7%	4.8%	5.0%	8.2%	9.3%	7.2%	9.3%	**87.3%**
South West	4.1%	1.0%	0.9%	3.1%	9.3%	3.9%	3.6%	5.0%	6.7%	6.1%	4.7%	12.8%	5.5%	8.4%	9.4%	7.2%	8.2%	**87.2%**
W. Midlands	3.9%	0.9%	0.9%	2.9%	9.2%	3.9%	3.5%	4.9%	6.7%	6.2%	4.7%	5.2%	13.7%	8.3%	9.5%	7.5%	8.2%	**86.3%**
North West	3.6%	0.8%	0.8%	2.8%	10.7%	3.8%	3.2%	4.6%	6.3%	5.8%	4.5%	4.6%	4.7%	19.5%	9.6%	7.0%	7.6%	**80.5%**
Wales	3.5%	0.9%	0.8%	3.2%	9.5%	3.9%	3.1%	4.4%	6.4%	5.6%	4.3%	4.4%	4.7%	8.4%	22.3%	6.8%	7.8%	**77.7%**
Scotland	3.6%	0.8%	0.8%	2.9%	9.7%	3.8%	3.3%	4.5%	6.5%	6.0%	4.4%	4.5%	4.8%	8.0%	9.0%	19.1%	8.0%	**80.9%**
N. Ireland	3.6%	0.8%	0.8%	2.8%	8.6%	3.7%	3.2%	4.6%	6.3%	5.7%	5.4%	4.5%	4.6%	7.7%	9.0%	6.9%	21.7%	**78.3%**
To	**73.0%**	**25.6%**	**23.7%**	**52.1%**	**147.4%**	**57.8%**	**50.8%**	**79.4%**	**103.8%**	**91.3%**	**71.3%**	**70.9%**	**72.9%**	**121.2%**	**141.4%**	**105.3%**	**122.6%**	**83.0%**

The previous connectedness results were for a particular time period. Figures 5 and 6 show how the connectedness measures are changing over time. They plot the estimates of *connectedness to* and *connectedness from* measures for all variables. To aid in visualisation, they have been standardised to 1.0 at the beginning of the sample, although we note that this might be interpreted as exaggerating the importance of the time-variation that we observe below given that some regions may be starting from a lower level.

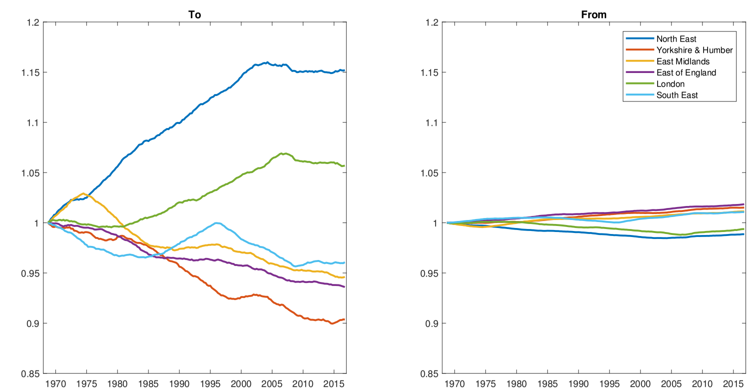
Connectedness measures can increase or decrease over time. But, for $h = 1$ (panels (a) and (c) of Figure 5), we are almost never seeing them decrease. Overall there is a pattern of a slight increase in connectedness over time. For the regional GVA growth variables, this increase tends to be larger in the *connectedness from* measures. However, there is one prominent exception. This is the North East of England which saw a substantial increase in its *connectedness to* measure. It is worth noting that, even with this increase, the North East still has a low value of this connectedness measure relative to the other regions.

With regards to the additional UK quarterly macroeconomic variables, there are substantial increases in the *connectedness to* measures for the oil price and the exchange rate. The impact of these variables on the UK regions seems to be increasing over time. But the *connectedness from* measures are basically unchanged over time.

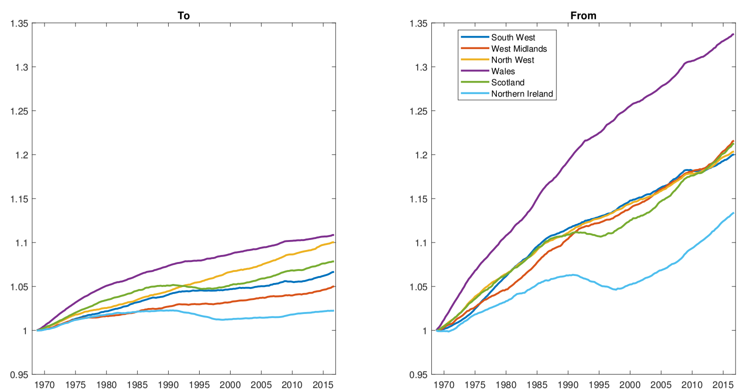
Figure 6 repeats the analysis for the longer $h = 20$ forecast horizon. For the additional quarterly macroeconomic indicators such as the oil price, we obtain similar findings as before. That is, the only substantive changes in connectedness measures are the *connectedness to* measures for the exchange rate and the oil price. However, for the regional GVA growth variables results with $h = 20$ are very different than we found with $h = 1$. In all cases the *connectedness from* measures are approximately constant over time. However, with two exceptions, the *connectedness to* measures are actually decreasing over time. The two exceptions are the North East and London. As before, the North East's *connectedness to* measure is increasing substantially over time. London is seeing a slight increase in its *connectedness to* measure indicating a small increase in its impact on other regions.



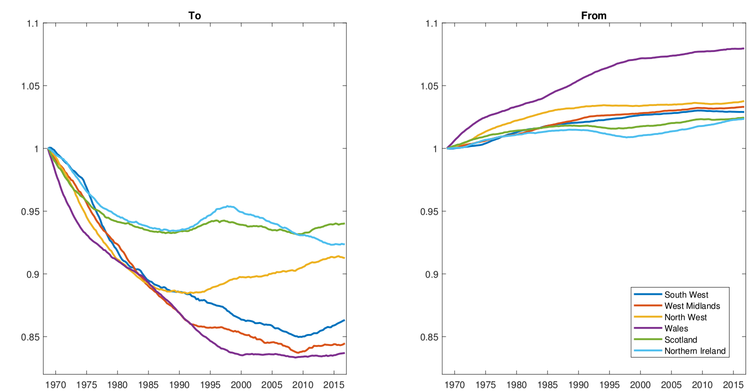
(a) Connectedness Measures: Change over Time, $h = 1$



(b) Connectedness Measures: Change over Time, $h = 20$

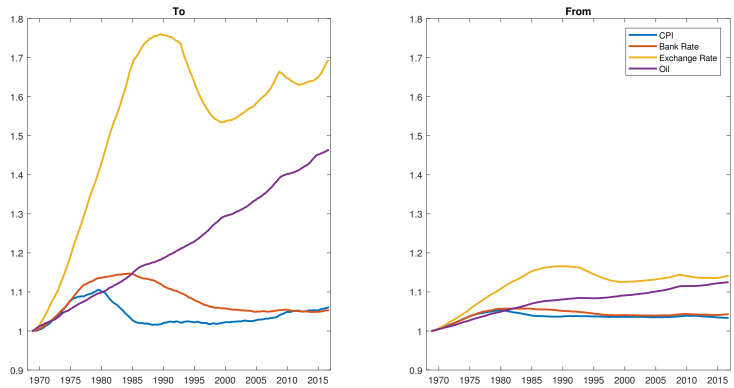


(c) Connectedness Measures: Change over Time, $h = 1$

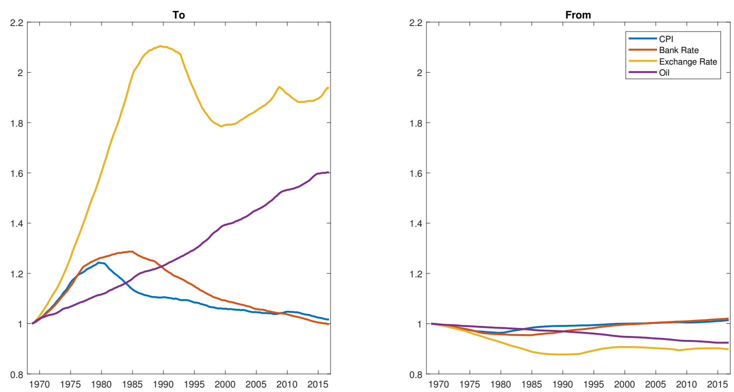


(d) Connectedness Measures: Change over Time, $h = 20$

Figure 5: Regional Connectedness Measures



(a) Connectedness Measures: Change over Time, $h = 1$



(b) Connectedness Measures: Change over Time, $h = 20$

Figure 6: Connectedness Measures: Additional Macroeconomic Indicators

4.3 Nowcasts of Quarterly Regional Growth

In this section, we investigate the forecasting performance of our 17-variable MF-VAR-SV. To evaluate its performance in real time, for both model estimation and forecast evaluation, we use first release GVA data as opposed to the final vintage data used in the preceding sub-sections.

4.3.1 Design of Forecasting Exercise

The forecast evaluation period begins in 2000 and ends with the latest (as of the time of writing) regional estimates for 2016 (published in December 2017); and all forecasts are recursive (i.e. produced using an expanding window of data) involving re-estimation of the VAR models. Given that real GVA data at the regional level have only been released since 2013 we confine this forecasting exercise to the nominal data; i.e., we focus on the timely production and evaluation of quarterly forecasts for nominal regional GVA growth only.

Using our model we produce timely and higher-frequency forecasts of quarterly regional GVA growth that anticipate the annual figures from the ONS, given that these data are released with a delay of at least one year. An advantage of our approach is that forecasts of quarterly and annual regional growth can be produced respecting and acknowledging the staggered publication and release of intra-year data on the regional and macroeconomic variables. That is, we produce forecasts of regional GVA acknowledging the fact that in real-time data have a ragged-edge at the end of the sample.

Specifically, we focus on the production of regional forecasts that are updated each time a new quarterly estimate of UK GVA growth is released by the ONS. During our out-of-sample window, the ONS have produced these UK-wide estimates around 60 days after the end of the reference quarter. At this point in time we also know the values of the other UK macroeconomic variables included in our model, including for the quarter of interest. For regional GVA, the ONS publish their estimates for annual regional growth in the fourth quarter of each year. Thus, it is only in Q4 of each year that we can update our regional forecasts to condition on the annual regional growth data for the previous year. This means that our forecasts produced in Q1-Q3 of any year are using regional data more than one year old.

In light of this release calendar, as new information accumulates we produce seven forecasts of the same fixed-event: annual regional GVA growth ending in year τ, with τ running from 2000 to 2016. These seven forecasts (with the timing advantage relative to the ONS's release of year τ regional data given in brackets) are made in:

1. Q1 of year τ (7 quarters)
2. Q2 of year τ (6 quarters)
3. Q3 of year τ (5 quarters)
4. Q4 of year τ (4 quarters)
5. Q1 of year $\tau + 1$ (3 quarters)
6. Q2 of year $\tau + 1$ (2 quarters)
7. Q3 of year $\tau + 1$ (1 quarter).

The preceding discussion explained the schedule we use to produce forecasts. We now turn to explaining precisely how the MF-VAR-SV can be used to produce them. We stress that we are always producing forecasts of annual growth rates since we wish to compare them to the actual annual data subsequently produced by the ONS. Thus, we take the quarterly forecasts made by the MF-VAR-SV and transform them to annual quantities using the intertemporal restriction, (2). The quantities on the right-hand-side of this equation are not observed, but we replace them with an appropriate combination of in-sample nowcasts and out-of-sample forecasts. This means that forecasts made in Q1 of year τ are constructed from an MF-VAR-SV estimated on a dataset that contains UK macroeconomic data for all four quarters of year $\tau - 1$ and annual regional data for year $\tau - 2$. This model produces forecasts of quarterly regional growth rates for years τ and $\tau - 1$ which are averaged using (2) to produce an annual forecast for year τ.

The forecasts made in Q2 and Q3 of year τ then work with MF-VAR-SVs that use the same regional data as the Q1 model, but the UK macroeconomic data now run through Q1 and Q2 of year τ, respectively. It is only by the forecast made in Q4 of year τ that the MF-VAR-SV will also include regional data for year $\tau - 1$, meaning that these data no longer have to be forecast.

The forecast of regional growth in year τ made in Q1 of year $\tau+1$ is the first forecast we make that is conditional on data for UK GVA growth for all of year τ. Subsequent forecasts of regional growth in year τ will additionally contain UK data from the initial part of year $\tau + 1$. Using information from year $\tau + 1$ to forecast year τ quantities is unusual (in essence, we are backasting). But to the extent that these year $\tau + 1$ updates also contain revisions to UK data in year τ it may be helpful. For this reason, we do compute the Q2 and Q3 of year $\tau + 1$ forecasts. We do not compute an eighth forecast, in Q4 of year $\tau + 1$, given that during this quarter, albeit near the end, ONS finally publish their own estimates for year τ regional GVA, thereby rendering this eighth forecast superfluous.

4.3.2 Results of Forecasting Exercise

We use root mean square forecast errors (RMSFEs) as a measure of the quality of the seven sets of point (conditional mean) forecasts. To evaluate the quality of the entire predictive densities the models are producing, we use log scores (i.e. sums of log predictive likelihoods). To provide an indication of the size of the benefits of conditioning the regional forecasts on within-year UK data and exploiting inter-regional dynamics, we also present results for a simple benchmark which lacks these features. This benchmark uses individual AR(1) models for each region. For these, estimation and forecasting is carried out using non-informative prior Bayesian methods. These are equivalent to ordinary least squares methods. We also investigated the significance of forecast improvements relative to the AR(1) benchmark using the Diebold-Mariano test of equal predictability. Since the hypothesis of equal predictability was always rejected in favour of our approach, we do not report them here.

Tables 4 and 5 contain the log scores and RMSFEs, respectively, for our forecast comparison exercise. Note first that all of the seven differently timed forecasts from the MF-VARs are more accurate than forecasts from the individual AR(1) models. This holds true regardless of region or whether we use RMSFEs or log scores as the measure of forecast performance. This offers strong additional reassurance that mixed frequency methods are of great use with our data set.

A second point worth noting is that we see a general tendency for forecast accuracy to increase as we move from Q1 through to Q4 of year τ. In particular, across all regions and both forecasting metrics, we see forecast accuracy gains of around 10% for the forecast computed in Q4 of year τ relative to the forecast produced one quarter earlier. This is reassuring, given that it is in Q4 of year τ that the regional data for year $\tau - 1$ become available. Thus, the evidence suggests that clear accuracy gains are had to be had if we wait for publication of both last year's regional data and for three quarters of current year UK data, before computing current year regional forecasts using our MF-VAR-SV models. However, the results in Tables 4 and 5 do not suggest that it is really worth waiting an additional quarter (until Q1 of year $\tau + 1$) for publication of the final quarter's data for UK growth ending in year τ. Accuracy, if anything, is slightly worse for the forecasts in rows 5 to 7 in the tables which also condition on available UK GVA growth in the last quarter of year τ. This suggests that the costs of using a forecast of the latter (as rows 1 to 4 in the tables do) are low from the perspective of regional forecast accuracy.

Overall, our forecasting results suggest that, especially towards the end of the year of interest (i.e. in Q4 of year τ), the econometric methodology developed in this paper can be used to provide reliable and timely forecasts of regional GVA growth at a higher frequency than is possible with conventional methods. In addition to providing more timely indicators of regional growth, this serves as a reassuring check on the quality of the regional growth estimates produced in this paper.

Table 4: Log Scores for Nominal GVA Growth Forecasts, 2000-2016

	North East	York. and H	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland
1. Q1 in year τ	1.31	1.37	1.33	1.18	1.07	1.23	1.23	1.28	1.12	1.07	1.16	0.96
2. Q2 in year τ	1.33	1.38	1.36	1.20	1.05	1.23	1.25	1.29	1.13	1.07	1.17	0.97
3. Q3 in year τ	1.33	1.40	1.37	1.22	1.04	1.23	1.26	1.30	1.14	1.09	1.19	0.99
4. Q4 in year τ	1.46	1.52	1.44	1.29	1.16	1.30	1.36	1.38	1.23	1.15	1.25	1.06
5. Q1 in year $\tau+1$	1.47	1.51	1.46	1.30	1.12	1.29	1.36	1.37	1.21	1.15	1.23	1.06
6. Q2 in year $\tau+1$	1.42	1.44	1.37	1.25	1.06	1.21	1.24	1.31	1.20	1.12	1.21	1.05
7. Q3 in year $\tau+1$	1.44	1.47	1.40	1.31	1.09	1.27	1.31	1.35	1.20	1.12	1.21	1.05
AR(1) (Non-informative)	0.56	0.56	0.55	0.52	0.53	0.54	0.54	0.56	0.56	0.55	0.56	0.52

Table 5: RMSFEs for Nominal GVA Growth Forecasts, 2000-2016

	North East	York. and H	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland
1. Q1 in year τ	0.067	0.060	0.064	0.070	0.078	0.066	0.069	0.060	0.073	0.071	0.063	0.087
2. Q2 in year τ	0.066	0.059	0.061	0.068	0.080	0.065	0.067	0.059	0.072	0.070	0.061	0.085
3. Q3 in year τ	0.064	0.056	0.059	0.066	0.078	0.065	0.064	0.058	0.069	0.067	0.058	0.080
4. Q4 in year τ	0.051	0.045	0.052	0.057	0.064	0.057	0.053	0.048	0.056	0.057	0.050	0.069
5. Q1 in year $\tau+1$	0.050	0.045	0.050	0.055	0.067	0.058	0.053	0.049	0.059	0.057	0.052	0.069
6. Q2 in year $\tau+1$	0.055	0.052	0.058	0.061	0.075	0.066	0.065	0.056	0.060	0.061	0.055	0.071
7. Q3 in year $\tau+1$	0.053	0.049	0.056	0.055	0.071	0.060	0.059	0.051	0.059	0.061	0.054	0.070
AR(1) (Non-informative)	0.134	0.133	0.136	0.142	0.139	0.137	0.136	0.133	0.133	0.134	0.133	0.140

5 Conclusions

Economists studying the regions of the UK have historically had to work with low frequency, annual data, often with limited historical coverage, rendering it hard to investigate issues such as the connectedness of regions at higher frequencies or understand how regions may enter and exit recessions differently. Policymakers have had to suffer from a lack of high frequency regional estimates and from long release delays which mean they are making decisions very much looking through the rear-view mirror (see Bean, 2007). We hope the output of this paper - a quarterly regional database from 1970 which is updated online each quarter to provide up-to-date nowcasts of regional economic growth - is found useful by economists, and regional economic policymakers alike.

To do this, we have developed a mixed frequency VAR that allows information from quarterly frequency (and more timely) UK GVA data to update the regional data throughout the year. One key econometric contribution is the inclusion of the cross-sectional restriction describing the relationship between (observed) UK quarterly GVA growth and (unobserved) regional quarterly growth rates. Another contribution lies in the use of a machine learning method based on the Dirichlet-Laplace hierarchical prior for ensuring parsimony in the very non-parsimonious mixed frequency VAR.

Given that it is anticipated that early 2019 will see the ONS starting to produce 'Regional Short Term Indicators' at the quarterly frequency for the NUTS 1 regions, our next step will be to incorporate these new indicators, available over a sub-sample of our database, into our model. These data, we hope, will improve further our quarterly nowcasts (flash estimates) of quarterly regional GVA at the NUTS 1 level; and also ensure our model-based estimates remain consistent with ONS data and ongoing improvements to these. These new quarterly regional data from the ONS, that will be published with a delay of 3 to 4 months, will also be an additional useful resource for testing and validating the quarterly nowcasts that we will publish on the ESCoE website, considerably earlier than the ONS around 45 days after the end of the quarter.

Additional avenues of research developing this model further should include expanding the model to consider a wider range of indicators of regional economic activity (such as regional labour market and sectoral output data), a more granular geographic coverage, and perhaps even higher frequency, say monthly, data. The barrier to implementing these developments at this point is computational, and focus should turn to this challenge next.

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Appendices

In this set of appendices, we describe the data, provide full details of our econometric methods and present some supplementary empirical results.

A Data Appendix

This appendix summaries the data sources and construction of the estimation databases used in this paper. It describes the process of arriving at an annual dataset for nominal and real GVA for the 12 NUTS 1 regions (these are defined by the Classification of Territorial Units for Statistics) of the UK (excluding the UK Continental Shelf) from 1966 to 2016 that is as consistent as possible, given changes to accounting standards over the time period. Our regional nominal GVA data are measured at factor cost prior to 1996 and at basic prices from 1997. Our real GVA data utilise the ONS's balanced GVA data, GBA(B), for the period 1998-2016[16]; and in the earlier period we deflate our regional nominal GVA data by the UK wide deflator. We also extend our database to incorporate a number of additional indicators into our model. These include the US dollar to British pound exchange rate, the oil price, the Bank Rate and the Consumer Price Index. We focus in the main paper on latest vintage or final release data (at the time of writing the latest vintage is December 2017), as they reflect the ONS's latest, and we presume best, assessment of historical economic growth. However, for our real-time nowcasting/forecasting work we use first release (nominal) data to better simulate the situation of the analyst producing nowcasts/forecasts using our model in real-time.

A.1 Nominal GVA data: first release and latest (or final) vintage

The construction of first release nominal GVA (income approach) data used in this paper follows closely that of Koop et al. (2018).[17] This earlier work provides a database of (as close as possible to) first release nominal GVA growth for 9 regions of the UK, with the smaller number of regions constructed in this work reflecting the need for a dataset of growth rates for each region on a consistent geographical basis.

In our modelling framework in this paper, in contrast, we work at the current 12 region level. These regions reflect the NUTS 1 regions of the UK, with the exception of the extra-regio (or UK Continental Shelf) region, for reasons discussed in the paper. To construct a database of first release nominal GVA growth covering the period 1967 to 2016, we therefore had to combine the information available from 1995 onwards on first release nominal GVA growth available from the ONS with the historical first release data collected in Koop et al. (2018). The nature of the changes in geography used between the statistical office regions, in place prior to 1995, and the current NUTS 1 regions of the UK, in place since 1995, mean that for five regions, which in Koop et al. (2018) were combined into two regions, we assumed that these regions shared the same growth rate in this earlier period as the aggregate, geographically consistent, region that they were part of in Koop et al. (2018).

To illustrate this in more detail, in Koop et al. (2018) the North East and North West of England comprise two regions in the NUTS 1 classification. Under the old Statistical Office Region classification, in place prior to 1995, these two regions comprised two (different) regions, the North and North West. The old North region comprised the whole of the current North East region, alongside a part of what is now the North West region. We have no way of separating out economic activity in the old North region between these two parts of the region. Therefore, in our database, prior to 1995 we assume that both the North East and North West of England grew at the same annual rate. The only

[16] These data are 'balanced' in the sense of balancing the income and production approaches to measuring GVA.

[17] Available at `https://www.escoe.ac.uk/download/2601/`

other part of the UK affected by this change in geography is London, the South East and the East of England regions under the current statistical geography, which comprised the South East (and from 1978 was further split into Greater London and the Rest of the South East) and East Anglia (itself representing a proportion of the subsequent East of England region which also includes part of what was the South East region) under the old Statistical Office Region geography.

In order to reconcile these changing geographies in a consistent manner, we assumed that for the regions on which we have disaggregated data from 1995 onwards, but only aggregate data prior to this, the disaggregated regions grew at the same annual rate as the aggregate geographical area which they were part of on a consistent geographical basis prior to 1995.

Like Koop et al. (2018) our aim in putting together the database for the nowcasting and forecasting work in this paper was to use, as near as possible, first-release estimates of regional GVA and match these with the appropriate, similarly dated, data release for UK GVA. This strategy is in part motivated by our interest in nowcasting first release regional GVA estimates. But it also reflects the reality that final vintage data, e.g. the ONS's latest regional estimates, are not available over the whole sample period (i.e. the latest ONS data for nominal GVA(B) or GVA(I), published in December 2017, cover the period 1998-2016 or 1997-2016 only). So to get earlier data we inevitably have to look to earlier data vintages. In matching the regional data to the UK data we sought to minimise the cross-sectional aggregation error, as ideally the sum of the regional GVA data (including the UKCS) equals the annual sum of the quarterly UK data. But, we should emphasise (as is detailed in the data appendix for Koop et al. (2018)) that it was not possible to eradicate this measurement error for all years. Also, as described in the main paper, we chose to exclude the UKCS from our VAR models given its distinct time-series properties. This means that we should not expect, even absent measurement error, the cross-sectional constraint to be met exactly, as we show below.

As detailed in the data appendix to Koop et al. (2018) the first release regional nominal GVA data were matched from 1966–1996 against UK GVA data (at factor cost, seasonally adjusted (series: ABML)) again extracted from successive, similarly dated, national account data releases (obtained from the Bank of England's real-time database for nominal income; code CGCB[18]) with the secondary aim of minimising the cross-sectional aggregation measurement error of the sum of the regional data against the quarterly UK data when aggregated to the annual frequency. From 1997 the regional data are matched against successive, similarly dated (so that again the data vintages of the regional data match that of the UK data), releases of quarterly UK GVA estimates, at basic prices, from the ONS's "Second estimate of GDP" previously known as the "UK Output, Income and Expenditure" press release/bulletins. Figure A1 shows that the cross-sectional aggregation measurement error is time-varying and often less than zero. The average statistical discrepancy between 1966 and 1996 is -0.47%, between 1997 and 2016 it is -0.39%

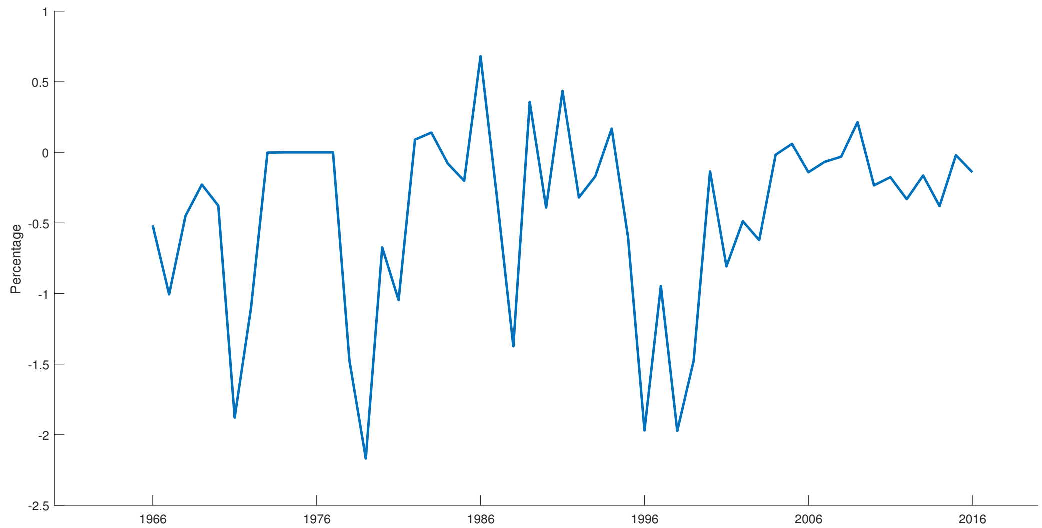
The final or latest vintage regional nominal GVA data are taken to be a combination (with the geographical reconcilition outlined above) of: (i) the historical 1966–1996 regional nominal GVA (income approach) data as released by the ONS[19] but without taking this back to first release, as described in Koop et al (2018), so that data revisions are accommodated[20]; and (ii) the December

[18]Available at `http://www.bankofengland.co.uk/statistics/Documents/gdpdatabase/nominal_income.xlsx`

[19]Available at `https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/adhocs/006226historiceconomicdataforregionsoftheuk1966to1996`

[20]The ONS's historical database picks up estimates from successive yearly publications of Regional Trends. But the publication lags vary, so that, for example, the 1966 GVA data come from the 1975 Regional Trends publication/vintage; while the 1970 data come from the 1976 Regional Trends publication. In general the publication lag shortens in the ONS's historical database, suggesting that more recent data have been through fewer annual rounds of revision. Our understanding, following email communication with ONS, is that this is in part because ONS chose to publish, in this historical database, the latest iteration for a given year rather than the first. When data were available, we sought to use the latest publication or data vintage for regional GVA in a given year.

Figure A.1: Discrepancy, by year, between the nominal UK Quarterly series and Regional Annual series (as % UK GVA)



2017 release of regional nominal GVA(B) data covering the period 1998–2016. The 1997 regional data are not available in balanced form, but the December 2017 data release from the ONS does provide estimates via the income approach and we use these. For the UK as a whole, the February 2018 vintage (of series AMBL) was taken as the latest vintage for quarterly nominal GVA.

A.2 Real GVA data: latest (or final) vintage

UK real quarterly GVA data on a comparable basis to the UK nominal quarterly GVA (series: ABML) data described above are produced by the ONS (series: ABMM), and can therefore be readily incorporated into our database. Again we use the February 2018 data vintage. Regional real GVA(B) data from 1998-2016 for each NUTS 1 (indeed NUTS 2 also) region of the UK are available from the ONS's December 2017 publication.[21]. But regional real GVA data are not available from this 2017 publication prior to 1998; indeed the latest release of the GVA(B) data used in this exercise is currently also the first release. However, using the database of latest release/vintage nominal GVA data for each NUTS 1 region (excl. UKCS) detailed above, it is possible to proxy the latest/final vintage estimates of real GVA growth in each of 12 NUTS 1 regions from 1966 to 1997 by deflating the nominal data using a UK aggregate-implied GDP deflator. This is a strong assumption, but without regional price data a necessary one, and assumes, in the period prior to 1998, common regional inflation. To summarise, our annual final vintage regional real GVA dataset combines the GVA(B) data produced for the first time in December 2017 (covering 1998–2016) with the final vintage, nominal regional data for the earlier period (1966–1997), deflated using a UK-wide measure of inflation.

[21]Data and a background methodology note are accessible here: `https://www.ons.gov.uk/economy/grossvalueaddedgva/bulletins/regionalgrossvalueaddedbalanceduk/1998to2016`

A.3 Additional macroeconomic indicators

In addition to GVA data for the UK as a whole and for the NUTS 1 regions, we include four additional quarterly indicators in our model. These are: the oil price (brent crude \$U/BBL), the Bank Rate (Bank of England base interest rate), consumer prices (UK CPI provided by ONS), and the exchange rate between the USA and the UK ($\$: \pounds$). These variables are not revised and so first release and final vintages are the same. The oil price and the exchange rate enter the VAR in log differenced form. For the CPI we use the log difference relative to the same quarter in the previous year. We downloaded the Bank of England interest rate data directly from the Bank[22], and the UK consumer price index data from the ONS[23]. The oil price data were taken from Thomson Reuters Datastream[24] as the quarterly average price. The US dollar : UK pound exchange rate series was downloaded from the Bank of England's Millennium Database[25].

B Technical Appendix

This appendix includes discussion of the state space model with state equations given by (1) and measurement equations given by (3), (4), and (5). In addition, we describe the stochastic volatility process given by (6), (7) and (8). We use an MCMC algorithm which draws from the full conditional posterior distributions. That is, we draw the VAR-SV model conditional on the states and the states conditional on the VAR coefficients and volatilities. Accordingly, this appendix describes econometric methods for these two parts separately. First, we describe methods for the VAR-SV, then for the states.

B.1 The VAR-SV

B.1.1 Model and Priors

We can rewrite (1) as a multivariate linear regression model:

$$\mathbf{y}_t = \mathbf{X}_t\beta + \epsilon_t, \epsilon_t \sim N(0, \Sigma_t), \tag{B.1}$$

where $\mathbf{X}_t = \mathrm{I}_n \otimes [1, \mathbf{y}'_{t-1}, \ldots, \mathbf{y}'_{t-p}]$ is an $n \times k$ matrix and $\beta = vec([\Phi_0, \Phi_1, \ldots, \Phi_p]')$ is a $k \times 1$ vector of coefficients. We can stack (B.1) over time $t = 1, \ldots T$, to get

$$\begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_T \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 \\ \vdots \\ \mathbf{X}_T \end{bmatrix} \beta + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_T \end{bmatrix}, \tag{B.2}$$

$$\mathbf{y} = \mathbf{X}\beta + \epsilon, \epsilon \sim N(0, \Sigma), \tag{B.3}$$

where $\Sigma = \mathrm{diag}(\Sigma_1, \ldots, \Sigma_T)$. We follow Bhattacharya et al. (2015) and use Dirichlet-Laplace priors for the β's. If we define $\beta = (\beta_1, \ldots, \beta_k)'$, then the priors follow

$$\beta_j \sim N(0, \psi_j^\beta \vartheta_{j,\beta}^2 \tau_\beta^2), \tag{B.4}$$

[22] https://www.bankofengland.co.uk/boeapps/database/Bank-Rate.asp

[23] https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceindices/current

[24] https://financial.thomsonreuters.com/en/products/tools-applications/trading-investment-tools/datastream-macroeconomic-analysis.html

[25] https://www.bankofengland.co.uk/statistics/research-datasets

$$\psi_j^\beta \sim \text{Exp}(\frac{1}{2}), \tag{B.5}$$

$$\vartheta_{j,\beta} \sim \text{Dir}(\alpha_\beta, \ldots, \alpha_\beta), \tag{B.6}$$

$$\tau_\beta \sim \text{G}(k\alpha_\beta, \frac{1}{2}). \tag{B.7}$$

The multivariate stochastic volatility specification used in this paper is given in (6), (7) and (8). We again follow Bhattacharya et al. (2015) and implement the Dirichlet-Laplace priors for the **a**'s and assume $i = 1, \ldots, m$

$$a_i \sim N(0, \psi_i^a \vartheta_{i,a}^2 \tau_a^2), \tag{B.8}$$

$$\psi_i^a \sim \text{Exp}(\frac{1}{2}), \tag{B.9}$$

$$\vartheta_{i,a} \sim \text{Dir}(\alpha_a, \ldots, \alpha_a), \tag{B.10}$$

$$\tau_a \sim \text{G}(m\alpha_a, \frac{1}{2}). \tag{B.11}$$

Finally, we assume

$$\omega_{h_j}^2 \sim \text{IG}(\nu_{h_j}, S_{h_j}), \quad \text{for } i = 1, \ldots, n. \tag{B.12}$$

B.1.2 The VAR-SV: MCMC Algorithm

Here we describe an MCMC algorithm for drawing from the VAR-SV parameters. In our MF-VAR-SV we draw from these conditional on the draws of the states (see below).

The conditional posterior for the VAR coefficients takes the following form:

$$\beta|\bullet \sim N(\hat{\beta}, \mathbf{K}_\beta^{-1}), \tag{B.13}$$

where

$$\mathbf{K}_\beta = \quad \mathbf{X}'\Sigma^{-1}\mathbf{X} + \mathbf{S}_\beta^{-1}, \quad \hat{\beta} = \mathbf{K}_\beta^{-1}(\mathbf{X}'\Sigma^{-1}\mathbf{y}), \tag{B.14}$$

where $\mathbf{S}_\beta = \text{diag}(\psi_1^\beta \vartheta_{1,\beta}^2 \tau_\beta, \ldots, \psi_k^\beta \vartheta_{k,\beta}^2 \tau_\beta^2)$.

The conditional posterior for **a** takes the following form:

$$\mathbf{a}|\bullet \sim N(\hat{\mathbf{a}}, \mathbf{K}_a^{-1}), \tag{B.15}$$

where

$$\mathbf{K}_a = \quad \mathbf{E}'\mathbf{D}^{-1}\mathbf{E} + \mathbf{S}_a^{-1}, \quad \hat{\mathbf{a}} = \mathbf{K}_a^{-1}(\mathbf{E}'\mathbf{D}^{-1}\epsilon), \tag{B.16}$$

where $\mathbf{S}_a = \text{diag}(\psi_1^a \vartheta_{1,a}^2 \tau_a, \ldots, \psi_m^a \vartheta_{m,a}^2 \tau_a^2)$, $\mathbf{D} = \text{diag}(\mathbf{D}_1, \ldots, \mathbf{D}_T)'$ and, assuming $n = 3$, an example of the **E** matrix is

$$\mathbf{E}_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ -\epsilon_{1,t} & 0 & 0 & 0 & 0 & 0 \\ 0 & -\epsilon_{1,t} & -\epsilon_{2,t} & 0 & 0 & 0 \\ 0 & 0 & 0 & -\epsilon_{1,t} & -\epsilon_{2,t} & -\epsilon_{3,t} \end{bmatrix}, \tag{B.17}$$

where **E** is the stacked version from $t = 1, \ldots, T$. For more information about constructing this **E** matrix, see Chan (2017, pp. 130-131).

To draw the log volatilities, we follow Chan and Eisenstat (2017) and apply the auxiliary mixture sampler of Kim et al. (1998) in conjunction with the precision sampler to sequentially draw each slice of $\mathbf{h}_{i,\bullet} = (h_{i,1}, \ldots, h_{i,T})'$, for $i = 1, \ldots, n$. See Chan and Hsiao (2014) and Cross and Poon (2016) for details.

To draw the initial condition $\mathbf{h}_0$, we follow Chan and Eisenstat (2017) and use

$$\mathbf{h}_0|\bullet \sim N(\hat{\mathbf{h}}_0, \mathbf{K}_{\mathbf{h}_0}^{-1}), \tag{B.18}$$

where

$$\mathbf{K}_{\mathbf{h}_0} = \quad \mathbf{V}_h^{-1} + \Sigma_h^{-1} \quad , \quad \hat{\mathbf{h}}_0 = \mathbf{K}_{\mathbf{h}_0}^{-1}(\mathbf{V}_h^{-1}\mathbf{a}_h + \Sigma_h^{-1}\mathbf{h}_1). \tag{B.19}$$

To draw Σ_h we note that $\omega_{h_i}^2$ are conditionally independent and follow

$$\omega_{h_j}^2|\bullet \sim IG(\nu_{h_j} + \tfrac{T}{2}, S_{h_j} + \tfrac{1}{2}\textstyle\sum_{t=1}^{T}(h_{j,t} - h_{j,t-1})^2), \quad \text{for } j = 1, \ldots, n. \tag{B.20}$$

As for $\psi_j^\beta, \vartheta_{j,\beta}, \tau_\beta$, following Bhattacharya et al. (2015), the conditional posterior distributions are

$$(\psi_j^\beta)^{-1}|\bullet \sim iG(\tfrac{\vartheta_{j,\beta}\tau_\beta}{|\beta_j|}, 1), \quad \text{for } j = 1, \ldots, k \tag{B.21}$$

$$\tau_\beta|\bullet \sim GIG(k(\alpha_\beta - 1), 1, 2\sum_{j=1}^{K}\frac{|\beta_j|}{\vartheta_{j,\beta}}), \tag{B.22}$$

$$R_{j,\beta}|\bullet \sim GIG(\alpha_\beta - 1, 1, 2|\beta_j|), \quad \text{for } j = 1, \ldots, k \tag{B.23}$$

and

$$\vartheta_{j,\beta} = \frac{R_{j,\beta}}{\sum_{j=1}^{k} R_{j,\beta}}. \tag{B.24}$$

We use notation where GIG is the generalised inverse Gaussian distribution; and to simulate a draw from this distribution we implement the algorithm by Devroye (2014). iG is the Inverse Gaussian distribution.

Similarly, to draw $\psi_i^a, \vartheta_{i,a}, \tau_a$ we use the following conditional posteriors:

$$(\psi_i^a)^{-1}|\bullet \sim iG(\tfrac{\vartheta_{i,a}\tau_a}{|a_i|}, 1), \quad \text{for } i = 1, \ldots, m \tag{B.25}$$

$$\tau_a|\bullet \sim GIG(m(\alpha_a - 1), 1, 2\sum_{i=1}^{m}\frac{|a_j|}{\vartheta_{i,a}}), \tag{B.26}$$

$$R_{i,a}|\bullet \sim GIG(\alpha_a - 1, 1, 2|a_i|), \quad \text{for } i = 1, \ldots, m \tag{B.27}$$

and

$$\vartheta_{i,a} = \frac{R_{i,a}}{\sum_{i=1}^{m} R_{i,a}}. \tag{B.28}$$

B.1.3 The Homoskedastic VAR

To estimate the time-invariant version of the VAR, where $\Sigma_t^{-1} = \mathbf{L}'\mathbf{D}^{-1}\mathbf{L}$, we restrict the diagonal elements of $\mathbf{D}_t$ to have time-invariant variances, such that

$$\mathbf{D}_t = \begin{bmatrix} \sigma_1^2 & 0 & & 0 \\ 0 & \ddots & & \\ & & \ddots & 0 \\ 0 & & 0 & \sigma_n^2 \end{bmatrix}. \tag{B.29}$$

We assume the priors for these variances to be

$$\sigma_i^2 \sim IG(\nu_i, S_i), \quad \text{for } i = 1, \ldots, n. \tag{B.30}$$

Under these assumptions, we draw from:

$$\sigma_i^2|\bullet \sim IG(\nu_i + \frac{T}{2}, S_i + \frac{1}{2}\sum_{t=1}^{T} \tilde{y}_{i,t}^2), \tag{B.31}$$

where the $\tilde{y}_{i,t}$ are the elements of

$$\tilde{\mathbf{y}}_t = \mathbf{L}(\mathbf{y}_t - \mathbf{X}_t\beta). \tag{B.32}$$

All the other posterior draws are exactly same as for the VAR-SV.

B.1.4 Prior Hyperparameter Choices

The hyperparameters that we choose for both the VAR and VAR-SV are $\alpha_\beta = \alpha_a = \frac{1}{2}$, $\mathbf{a}_h = \mathbf{0}$, $\mathbf{V}_h = 10 \times \mathbf{I}_n$, $\nu_i = \nu_{h_j} = 5$ and $S_i = S_{h_j} = .01$. The priors for the variances of the stochastic volatility terms are standard and similar to those made in Chan and Eisenstat (2017). The choices for the Dirichlet-Laplace hyperparameters, α_β, α_a, are the relatively noninformative default choices suggested by Bhattacharya et al. (2015).

B.2 The Mixed Frequency State Space Model

To show how we add the mixed frequency aspect to the model and incorporate the cross-sectional restriction, we use a simple example where we have one quarterly frequency variable and two annual frequency variables and assume seven lags. Results extend to many regions and other lag lengths in a straightforward manner. In the context of our study, the quarterly variable is the UK GVA growth rate and the two annual frequency variables are the two regions' annual growth rates.

Our quarterly VAR can be written as:

$$\begin{bmatrix} y_t^{UK} \\ y_t^1 \\ y_t^2 \end{bmatrix} = \begin{bmatrix} \Phi_{qc} \\ \Phi_{ac} \end{bmatrix} + \begin{bmatrix} \Phi_{qq,1} & \Phi_{qa,1} \\ \Phi_{aq,1} & \Phi_{aa,1} \end{bmatrix} \begin{bmatrix} y_{t-1}^{UK} \\ y_{t-1}^1 \\ y_{t-1}^2 \end{bmatrix} + \ldots + \begin{bmatrix} \Phi_{qq,7} & \Phi_{qa,7} \\ \Phi_{aq,7} & \Phi_{aa,7} \end{bmatrix} \begin{bmatrix} y_{t-7}^{UK} \\ y_{t-7}^1 \\ y_{t-7}^2 \end{bmatrix} + \epsilon_t. \tag{B.33}$$

We can rearrange this equation into a state equation. First, we group the above VAR coefficients together as

$$\Phi_{qq} = \begin{bmatrix} \Phi_{qq,1}, & \Phi_{qq,2}, & \Phi_{qq,3} & ,\ldots, \Phi_{qq,7} \end{bmatrix}, \tag{B.34}$$

$$\Phi_{qa} = \begin{bmatrix} \Phi_{qa,1}, & \Phi_{qa,2}, & \Phi_{qa,3} & ,\ldots, \Phi_{qa,7} \end{bmatrix}, \tag{B.35}$$

$$\Phi_{aq} = \begin{bmatrix} \Phi_{aq,1} & ,\Phi_{aq,2} & ,\Phi_{aq,3} & ,\ldots, \Phi_{aq,7} \end{bmatrix}, \tag{B.36}$$

$$\Phi_{aa} = \begin{bmatrix} \Phi_{aa,1} & ,\Phi_{aa,2}, & \Phi_{aa,3} & ,\ldots, \Phi_{aa,7} \end{bmatrix}. \tag{B.37}$$

Then our state equation is

$$\mathbf{s}_t = \Gamma_s \mathbf{s}_{t-1} + \Gamma_z \mathbf{y}_{t-p:t-1}^{UK} + \Gamma_c + \Gamma_u u_{a,t}, \tag{B.38}$$

where $\mathbf{s}_t = (y_t^1, y_t^2, y_{t-1}^1, y_{t-1}^2, y_{t-2}^1, y_{t-2}^2, y_{t-3}^1, y_{t-3}^2, \ldots, y_{t-7}^1, y_{t-7}^2)'$ is a $z \times 1$ vector containing the regional variables and their lags and $\mathbf{y}_{t-p:t-1}^{UK} = (y_{t-7}^{UK}, \ldots, y_{t-1}^{UK})'$ contains lags of the UK variables.

Using the following definitions:

$$\Gamma_s = \begin{bmatrix} \Phi_{qq} & 0 \\ \mathbf{I} & 0 \end{bmatrix}_{z\times z}, \Gamma_z = \begin{bmatrix} \Phi_{aq} \\ 0 \end{bmatrix}_{z\times p}, \Gamma_c = \begin{bmatrix} \Phi_{ac} \\ 0 \end{bmatrix}_{z\times 1}, \Gamma_u = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}_{z\times 2}, \tag{B.39}$$

we can obtain the measurement equation:

$$y_t^{UK} = \Lambda_{qs}\mathbf{s}_t + \Phi_{qq}\mathbf{y}_{t-p:t-1}^{UK} + \Phi_{ac} + u_{q,t}, \tag{B.40}$$

where

$$\Lambda_{qs} = \begin{bmatrix} 0 & \Phi_{qa} \end{bmatrix}_{1\times z}. \tag{B.41}$$

When both the quarterly and annual variables are observed at time t, the measurement equation is

$$\begin{bmatrix} y_t^{1,A} \\ y_t^{2,A} \end{bmatrix} = \Lambda_{as}\mathbf{s}_t + \Lambda_z \mathbf{y}_{t-p:t-1}^{UK} + \Phi_{qc}, \tag{B.42}$$

where

$$\Lambda_{as} = \begin{bmatrix} 0 & \Phi_{qa} \\ & M \end{bmatrix}, \Lambda_z = [\begin{smallmatrix} \Phi_{qq} \\ 0 \end{smallmatrix}], \tag{B.43}$$

$$M = \begin{bmatrix} \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & 0 & 0 \\ 0 & \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & 0 \end{bmatrix}. \tag{B.44}$$

This incorporates the intertemporal restriction given in (2).

Finally, the cross-sectional restriction gives us an additional measurement equation. We have

$$y_t^{UK} = \mathbf{R}\mathbf{s}_t + \eta, \eta \sim N(0, \sigma_{cs}^2), \tag{B.45}$$

where

$$\mathbf{R} = \begin{bmatrix} \frac{1}{R} & \frac{1}{R} & 0 \end{bmatrix}_{1\times z}. \tag{B.46}$$

We assume a tight prior for the variance of the cross-sectional restriction $\sigma_{cs}^2 \sim IG(1000, .001)$, where the prior mean of the variance is close to zero.

Thus, we have a set of state equations given by (B.38) and measurement equations given by (B.40), (B.42) and (B.45). Thus, conditional on draws of the all the other parameters of the MF-VAR-SV described earlier in this Technical Appendix, we can use standard Bayesian MCMC methods to draw the states. We use the precision sampler methods of Chan (2017) to do so.

To compute the marginal likelihood, we use the methodology of Chan and Eisenstat (2017) and calculate the marginal likelihood based on the integrated likelihood (not the conditional likelihood).[26] In our study, each model's marginal likelihood estimate is computed using 100 parallel chains, each consisting of 5000 evaluations of the integrated likelihood.

C Empirical Appendix

C.1 Model specification results

Here we present some evidence in favour of our chosen specification. Note that we have two different nominal data sets: the first includes only nominal GVA growth variables, the second includes these variables plus the additional high frequency macroeconomic variables, x_t^{UK}, in the MF-VAR-SV. For each of these we also have final vintage and first or initial release versions of the data sets. We also have two versions of each model: one homoscedastic and one with multivariate stochastic volatility. For the real dataset we have a similar set of models, except that we only have final vintage data in the absence of real-time data for regional real GVA. All models have a lag length of 4. This choice is motivated by our use of quarterly data and an examination of marginal likelihoods.

The tables below present logs of marginal likelihoods for the various data sets and specifications for the final vintage and initial release versions of our nominal data; and for the final vintage versions of our real data. Note that we calculate marginal likelihoods in two ways: one using all the variables in the model and one using only the 12 UK regional growth variables. We consider the latter since these are our variables of interest and measures of model of fit in relation to them are of particular

[26] Traditionally, the marginal likelihood has been computed using the modified harmonic mean of the conditional likelihood. However, Chan and Grant (2015) note that this approach can lead to substantial bias in the estimates and tends to select the wrong model.

importance. Furthermore, a comparison across VAR dimensions can only be done by focusing on variables common to both dimensions. That is, it is not meaningful to compare a marginal likelihood of a 13 dimensional VAR to that of a 17 dimensional VAR; but it is meaningful to do such a comparison if the marginal likelihood is constructed using 12 variables which are common to both VARs.

It can be seen that, for all three data sets, there is strong evidence in favour both of stochastic volatility and of the benefit of adding in the additional macroeconomic variables. In light of this, when working with both nominal and real GVA growth data, we present results from the model with multivariate stochastic volatility augmented with the additional quarterly macroeconomic variables.

Table C.1: Logs of Marginal Likelihoods Using Nominal GVA Data: Final Vintage Data

Final Vintage Data, Numerical Standard Errors in Parentheses		
Models using only GVA growth variables		
	Only Regional Variables	All Variables
MF-VAR (No SV)	4107.9 (1.30)	4713.7 (0.60)
MF-VAR-SV	4393.98 (1.16)	5027.1 (0.90)
Models with additional variables		
	Only Regional Variables	All Variables
MF-VAR (No SV)	4153.3 (1.15)	3463.7 (3.38)
MF-VAR-SV	4544.4 (1.21)	4355.3 (1.67)

Table C.2: Logs of Marginal Likelihoods Using Nominal GVA Data: First Release Data

Initial Release Data, Numerical Standard Errors in Parentheses

Models using only GVA growth variables

	Only Regional Variables	All Variables
MF-VAR (No SV)	2826.5 (2.53)	3616.7 (1.72)
MF-VAR-SV	3332.9 (1.37)	3950.6 (1.35)

Models with additional variables

	Only Regional Variables	All Variables
MF-VAR (No SV)	3267.6 (1.20)	2621.2 (3.62)
MF-VAR-SV	3623.3 (1.18)	3594.7 (1.46)

Table C.3: Logs of Marginal Likelihoods Using Real GVA Data: Final Vintage Data

Final Vintage Data, Numerical Standard Errors in Parentheses

Models using only GVA growth variables

	Only Regional Variables	All Variables
MF-VAR (No SV)	4548.5 (0.47)	4955.7 (0.51)
MF-VAR-SV	4982.9 (0.61)	5517.7 (0.60)

Models with additional variables

	Only Regional Variables	All Variables
MF-VAR (No SV)	4517.2 (0.45)	3649 (2.77)
MF-VAR-SV	4975.5 (0.67)	4589.8 (1.60)

C.2 Additional Connectedness Results

In the body of the paper, tables of posterior means of connectedness measures were reported. To give the reader a feeling for estimation uncertainty, Tables C.4 and C.5 present the 16th and 84th percentiles, respectively, of the posteriors of the connectedness measures. These tables are based on the nominal GVA data and are for one quarter ahead measures in 2016Q4. Results for other horizons and time periods are similar. It is worth noting that these credible intervals are fairly wide indicating a fair degree of estimation uncertainty.

For the reader interested in what the connectedness tables look like for real GVA, focusing on the posterior means, we provide Tables C.6 and C.7. Note that, just as with the nominal GVA data, the oil price has the largest impact.

Table C.4: Connectedness Estimates for 2016Q4, 1 quarter ahead forecast horizon, 16th percentile. Nominal GVA Data

	UK	CPI	Bank rate	Ex. rate	Oil price	North E.	York. and H.	E. Midlands	E. of England	London	South E.	South West	West Midlands	North West	Wales	Scotland	N. Ireland	**From**
UK	46.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	**0.3%**
CPI	0.0%	54.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	**0.3%**
Bank rate	0.0%	0.0%	60.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
Ex. rate	0.0%	0.0%	0.0%	53.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	**0.3%**
Oil price	0.0%	0.0%	0.0%	0.0%	53.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	**0.3%**
North E.	0.0%	0.0%	0.0%	0.0%	0.0%	51.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	**0.3%**
York. and H.	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	60.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
E. Midlands	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	39.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	**0.5%**
E. of England	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	43.8%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	**0.6%**
London	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	51.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.4%**
South E.	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	47.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	**0.5%**
South West	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	51.2%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.4%**
West Midlands	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	56.2%	0.0%	0.0%	0.0%	0.0%	**0.4%**
North West	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	46.2%	0.1%	0.0%	0.0%	**0.6%**
Wales	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%	52.3%	0.0%	0.1%	**0.6%**
Scotland	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	54.3%	0.0%	**0.5%**
N. Ireland	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	60.2%	**0.5%**
To	**0.1%**	**0.0%**	**0.0%**	**0.2%**	**1.1%**	**0.1%**	**0.1%**	**0.4%**	**0.6%**	**0.4%**	**0.3%**	**0.3%**	**0.3%**	**0.6%**	**0.9%**	**0.6%**	**0.8%**	0.4%

Table C.5: Connectedness Estimates for 2016Q4, 1 quarter ahead forecast horizon, 84th percentile. Nominal GVA Data

	UK	CPI	Bank rate	Ex. rate	Oil price	North E.	York. and H.	E. Midlands	E. of England	London	South E.	South West	West Midlands	North West	Wales	Scotland	N. Ireland	**From**
UK	84.0%	1.2%	1.3%	0.7%	0.9%	3.0%	2.0%	11.6%	13.1%	6.4%	10.0%	4.1%	2.8%	2.7%	2.6%	1.5%	6.5%	**70.3%**
CPI	1.8%	88.8%	4.1%	1.5%	0.5%	0.2%	0.5%	11.5%	9.0%	4.0%	1.0%	0.9%	0.9%	1.2%	11.1%	3.6%	4.5%	**56.4%**
Bank rate	1.9%	4.1%	91.2%	0.3%	0.2%	0.7%	0.9%	7.8%	11.9%	3.8%	3.5%	1.0%	1.1%	1.4%	2.3%	3.5%	2.2%	**46.6%**
Ex. rate	0.2%	0.2%	0.1%	86.7%	15.0%	5.2%	5.9%	1.3%	1.3%	1.9%	1.6%	3.2%	1.9%	2.6%	11.8%	4.9%	4.2%	**61.5%**
Oil price	0.0%	0.0%	0.0%	3.7%	84.2%	2.6%	1.1%	3.0%	4.2%	6.1%	3.2%	2.6%	2.7%	15.7%	9.6%	8.0%	3.2%	**65.8%**
North E.	0.9%	0.1%	0.2%	6.8%	14.1%	87.0%	0.8%	1.7%	2.4%	2.2%	1.9%	2.0%	1.6%	4.6%	12.4%	5.1%	4.7%	**61.5%**
York. and H.	0.7%	0.1%	0.2%	8.4%	7.2%	1.0%	90.2%	1.4%	4.1%	2.8%	1.8%	4.0%	3.4%	2.4%	2.9%	3.4%	2.2%	**46.1%**
E. Midlands	3.1%	2.3%	1.4%	1.6%	13.5%	1.6%	1.1%	76.2%	19.0%	10.1%	5.3%	5.3%	2.5%	6.7%	4.7%	3.6%	6.5%	**88.4%**
E. of England	2.6%	1.2%	1.7%	1.1%	13.9%	1.6%	2.4%	12.7%	77.0%	3.1%	2.7%	2.6%	2.7%	7.0%	13.7%	7.5%	6.4%	**82.9%**
London	1.3%	0.5%	0.5%	1.6%	19.3%	1.4%	1.7%	7.2%	3.4%	86.8%	3.0%	2.4%	3.7%	4.2%	4.0%	4.8%	3.3%	**62.3%**
South E.	2.4%	0.2%	0.6%	1.7%	13.7%	1.6%	1.4%	5.0%	3.6%	4.2%	84.6%	2.0%	1.9%	3.3%	2.9%	2.1%	23.8%	**70.4%**
South West	1.1%	0.2%	0.2%	3.7%	11.9%	1.8%	3.1%	5.0%	3.8%	3.4%	2.1%	86.1%	8.8%	6.6%	3.8%	1.9%	3.5%	**60.9%**
West Midlands	0.7%	0.2%	0.2%	2.0%	11.3%	1.2%	2.5%	2.4%	3.5%	4.7%	1.8%	7.9%	88.7%	3.3%	5.0%	4.2%	2.6%	**53.3%**
North West	0.4%	0.1%	0.1%	1.6%	27.6%	2.3%	1.0%	3.6%	5.1%	3.1%	1.9%	3.7%	2.1%	84.9%	14.0%	4.0%	3.0%	**73.6%**
Wales	0.3%	0.9%	0.2%	5.7%	17.3%	5.1%	1.0%	2.0%	7.9%	2.3%	1.3%	1.7%	2.5%	11.4%	84.1%	3.5%	4.0%	**67.2%**
Scotland	0.2%	0.4%	0.4%	3.1%	18.8%	2.7%	1.5%	2.1%	5.7%	3.8%	1.3%	1.2%	2.6%	4.7%	4.9%	88.5%	3.9%	**57.2%**
N. Ireland	0.8%	0.4%	0.2%	2.5%	8.0%	2.2%	0.9%	3.2%	4.7%	2.4%	12.0%	1.8%	1.5%	3.0%	5.0%	3.6%	87.8%	**52.2%**
To	**18.2%**	**11.9%**	**11.3%**	**46.1%**	**193.3%**	**34.2%**	**27.8%**	**81.6%**	**102.7%**	**64.4%**	**54.4%**	**46.4%**	**42.7%**	**80.8%**	**110.6%**	**65.3%**	**84.6%**	**63.3%**

Table C.6: Real GVA Growth Connectedness Estimates for 2016Q4, 1 quarter ahead forecast horizon

	UK	CPI	Bank rate	Ex. rate	Oil price	North E.	York. and H.	E. Midlands	E. of England	London	South E.	South West	West Midlands	North West	Wales	Scotland	N. Ireland	**From**
UK	68.9%	0.7%	0.7%	0.4%	0.7%	1.3%	1.1%	4.2%	4.9%	3.3%	4.6%	2.0%	1.3%	1.3%	1.1%	0.7%	2.9%	**31.1%**
CPI	0.8%	77.5%	2.1%	0.9%	0.3%	0.1%	0.3%	3.5%	2.5%	1.6%	0.5%	0.4%	0.4%	0.5%	4.4%	1.6%	2.3%	**22.5%**
Bank rate	0.8%	2.0%	78.7%	0.2%	0.1%	0.4%	0.6%	2.5%	5.6%	1.8%	1.8%	0.5%	0.5%	0.7%	1.0%	1.7%	1.0%	**21.3%**
Ex. rate	0.1%	0.2%	0.0%	71.3%	6.7%	2.3%	2.6%	0.7%	0.7%	0.9%	0.9%	1.7%	0.9%	1.4%	4.8%	2.6%	2.2%	**28.7%**
Oil price	0.0%	0.0%	0.0%	1.9%	70.7%	1.4%	0.6%	1.4%	1.9%	2.5%	1.5%	1.3%	1.4%	6.0%	4.1%	3.6%	1.5%	**29.3%**
North E.	0.4%	0.0%	0.1%	2.9%	5.9%	71.8%	0.5%	0.8%	1.1%	1.0%	1.0%	1.0%	0.8%	2.1%	5.5%	2.7%	2.5%	**28.2%**
York. and H.	0.3%	0.1%	0.2%	3.4%	3.5%	0.6%	77.8%	0.8%	2.0%	1.3%	1.0%	2.0%	1.6%	1.2%	1.4%	1.7%	1.1%	**22.2%**
E. Midlands	1.1%	0.8%	0.6%	1.0%	5.9%	0.9%	0.8%	63.0%	6.3%	4.2%	2.7%	2.4%	1.3%	3.1%	1.8%	1.6%	2.7%	**37.1%**
E. of England	1.0%	0.5%	1.0%	0.7%	6.2%	0.9%	1.5%	4.3%	65.0%	1.3%	1.2%	1.2%	1.3%	2.7%	5.0%	3.4%	2.8%	**35.0%**
London	0.7%	0.3%	0.3%	0.9%	7.2%	0.8%	1.0%	2.9%	1.5%	72.5%	1.6%	1.3%	1.9%	1.8%	1.6%	2.3%	1.6%	**27.5%**
South E.	1.1%	0.1%	0.4%	1.1%	6.1%	1.0%	0.9%	2.3%	1.6%	2.1%	68.5%	1.0%	0.8%	1.6%	1.3%	1.1%	8.9%	**31.5%**
South West	0.5%	0.1%	0.1%	2.0%	5.4%	1.0%	1.8%	2.1%	1.6%	1.6%	1.1%	71.5%	3.9%	3.0%	1.7%	0.9%	1.8%	**28.5%**
West Midlands	0.3%	0.1%	0.1%	1.1%	5.6%	0.7%	1.3%	1.1%	1.7%	2.3%	0.9%	3.5%	74.3%	1.6%	2.1%	2.0%	1.3%	**25.7%**
North West	0.2%	0.1%	0.1%	0.9%	11.5%	1.3%	0.6%	1.7%	2.0%	1.5%	1.0%	1.9%	1.1%	68.1%	4.8%	1.8%	1.5%	**31.9%**
Wales	0.1%	0.5%	0.1%	2.8%	7.6%	2.5%	0.6%	0.8%	3.0%	1.1%	0.7%	0.9%	1.2%	3.9%	70.2%	1.7%	2.2%	**29.8%**
Scotland	0.1%	0.2%	0.2%	1.9%	8.2%	1.6%	1.0%	1.0%	2.6%	1.8%	0.7%	0.6%	1.4%	2.2%	2.4%	71.8%	2.3%	**28.2%**
N. Ireland	0.3%	0.3%	0.1%	1.5%	3.9%	1.3%	0.6%	1.4%	2.0%	1.2%	4.5%	1.1%	0.8%	1.6%	2.7%	2.2%	74.6%	**25.4%**
To	**7.9%**	**5.8%**	**6.2%**	**23.6%**	**84.9%**	**18.2%**	**15.7%**	**31.4%**	**41.1%**	**29.7%**	**25.6%**	**23.0%**	**20.4%**	**34.6%**	**45.5%**	**31.6%**	**38.6%**	**28.5%**

Table C.7: Real GVA Growth Connectedness Estimates for 2016Q4, 20 quarter ahead forecast horizon

	UK	CPI	Bank rate	Ex. rate	Oil price	North E.	York. and H.	E. Midlands	E. of England	London	South E.	South West	West Midlands	North West	Wales	Scotland	N. Ireland	**From**
UK	21.0%	3.2%	3.3%	3.7%	8.5%	3.5%	3.0%	4.8%	6.3%	5.2%	4.8%	3.9%	3.8%	6.2%	7.1%	5.3%	6.6%	**79.0%**
CPI	5.1%	29.7%	9.3%	5.3%	8.4%	2.3%	1.8%	4.3%	4.7%	3.6%	2.6%	2.2%	2.3%	3.9%	6.4%	3.6%	4.5%	**70.3%**
Bank rate	8.3%	7.2%	28.6%	5.5%	7.4%	2.3%	2.0%	4.2%	6.3%	3.6%	3.3%	2.3%	2.4%	3.8%	5.2%	3.5%	4.2%	**71.4%**
Ex. rate	3.8%	2.7%	2.2%	22.4%	10.1%	3.9%	3.4%	3.7%	5.0%	4.5%	3.7%	3.8%	3.7%	6.3%	8.6%	5.9%	6.4%	**77.6%**
Oil price	3.3%	1.6%	1.6%	3.6%	19.0%	4.9%	3.4%	4.3%	6.5%	5.3%	4.6%	4.2%	4.7%	8.3%	9.1%	7.6%	7.9%	**81.0%**
North E.	4.0%	0.9%	1.1%	3.4%	9.6%	11.9%	3.9%	4.6%	6.5%	5.6%	4.8%	4.8%	5.0%	8.4%	9.9%	7.6%	8.1%	**88.1%**
York. and H.	4.0%	0.9%	1.0%	3.5%	9.2%	4.2%	11.6%	4.7%	6.6%	5.6%	4.9%	5.0%	5.1%	8.3%	9.5%	7.5%	8.3%	**88.4%**
E. Midlands	4.0%	1.0%	1.1%	3.2%	9.6%	4.1%	3.8%	12.2%	7.1%	6.0%	5.0%	5.0%	5.0%	8.2%	9.2%	7.5%	8.3%	**87.8%**
E. of England	4.1%	0.9%	1.1%	3.0%	9.4%	3.9%	3.8%	5.1%	16.2%	5.5%	4.8%	4.6%	4.8%	8.0%	9.2%	7.6%	8.0%	**83.8%**
London	4.1%	0.9%	1.0%	3.1%	9.7%	4.0%	3.7%	4.8%	6.4%	15.6%	4.9%	4.6%	4.9%	7.9%	9.0%	7.4%	7.9%	**84.4%**
South E.	4.2%	0.9%	1.0%	3.1%	9.5%	4.1%	3.7%	4.7%	6.5%	5.9%	13.5%	4.6%	4.9%	8.1%	8.9%	7.4%	9.0%	**86.5%**
South West	3.9%	0.9%	1.0%	3.3%	9.4%	4.1%	3.9%	4.7%	6.5%	5.6%	4.8%	13.8%	5.3%	8.3%	9.2%	7.3%	8.1%	**86.2%**
West Midlands	3.9%	0.9%	1.0%	3.2%	9.4%	4.1%	3.8%	4.6%	6.4%	5.8%	4.8%	5.1%	14.6%	8.0%	9.1%	7.4%	7.9%	**85.4%**
North West	3.6%	0.8%	0.9%	2.9%	10.9%	3.9%	3.5%	4.4%	6.2%	5.2%	4.5%	4.6%	4.6%	20.2%	9.1%	7.0%	7.4%	**79.8%**
Wales	3.5%	0.9%	0.9%	3.4%	9.7%	4.1%	3.4%	4.2%	6.2%	5.2%	4.3%	4.3%	4.5%	8.0%	22.9%	6.8%	7.7%	**77.1%**
Scotland	3.6%	0.8%	0.9%	3.1%	9.8%	4.0%	3.6%	4.3%	6.4%	5.5%	4.5%	4.3%	4.7%	7.7%	8.9%	19.8%	7.9%	**80.2%**
N. Ireland	3.6%	0.8%	0.9%	3.1%	8.7%	3.9%	3.5%	4.4%	6.2%	5.3%	5.4%	4.4%	4.6%	7.5%	8.8%	7.0%	22.0%	**78.0%**
To	**67.0%**	**25.4%**	**28.4%**	**56.4%**	**149.2%**	**61.3%**	**54.4%**	**71.9%**	**99.6%**	**83.2%**	**71.7%**	**67.8%**	**70.1%**	**116.9%**	**137.3%**	**106.4%**	**118.1%**	81.5%

C.3 Credible Intervals for the Quarterly Regional Estimates

To convince the user that our econometric methodology is producing accurate estimates, Figures C.1 and C.2 plot quarterly estimates of annualised real regional GVA growth rates along with credible intervals which cover the 16th through 84th percentiles. Note that, for the reasons discussed in the body of the paper, these figures plot annual growth rates. Figures C.3 and C.4 present analogous results for nominal regional GVA growth.

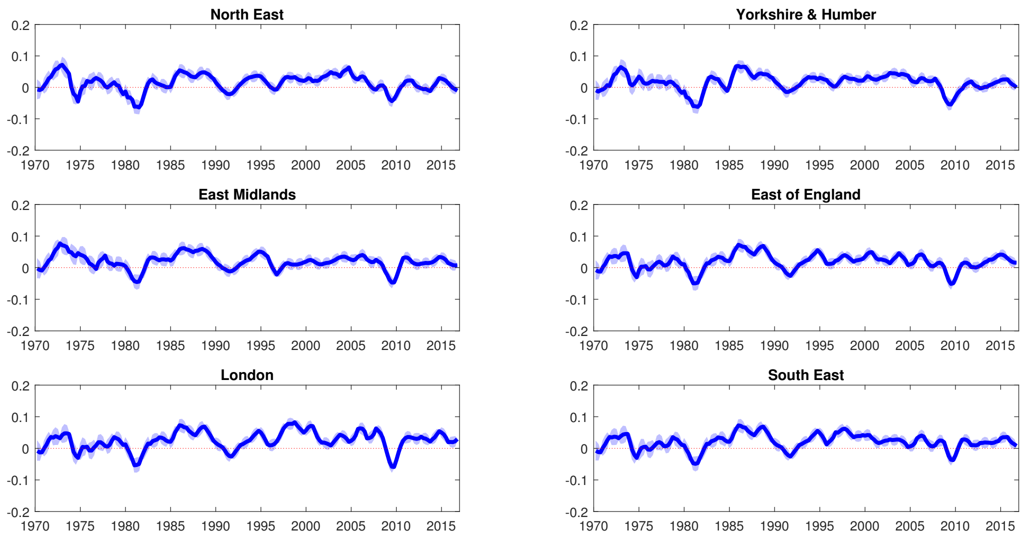


Figure C.1: Regional Real GVA Growth Rates: Estimates and Credible Intervals

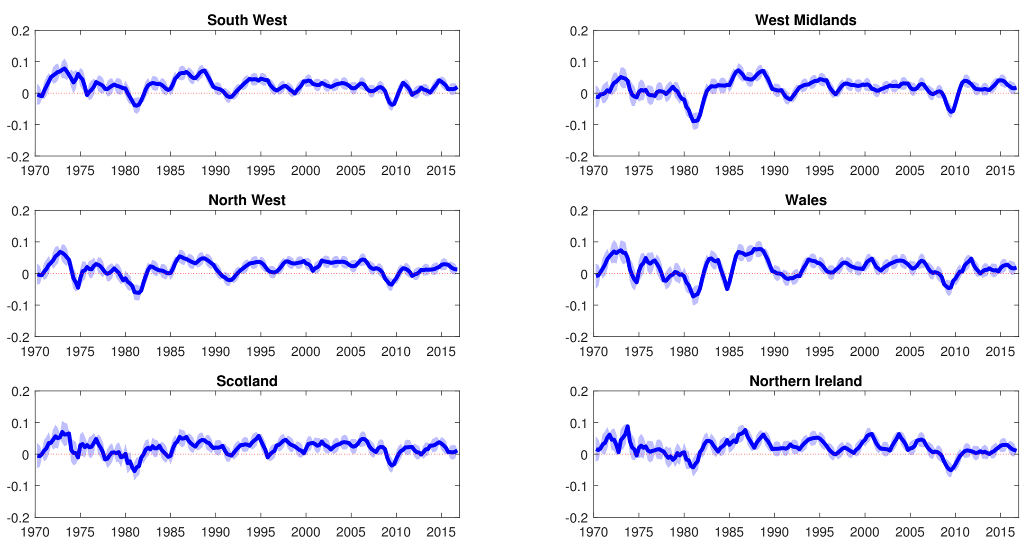


Figure C.2: Regional Real GVA Growth Rates: Estimates and Credible Intervals (cont.)

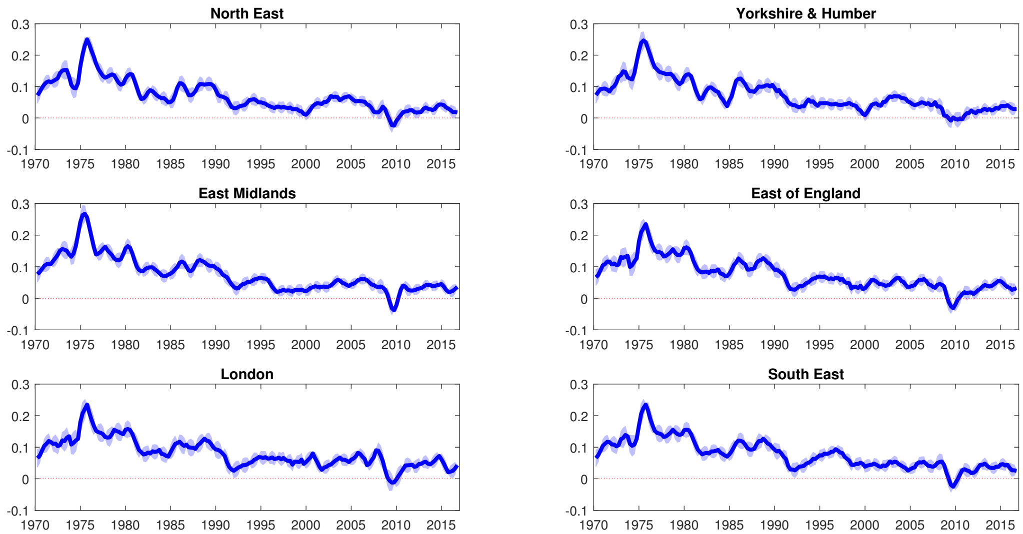


Figure C.3: Regional Nominal Growth Rates: Estimates and Credible Intervals

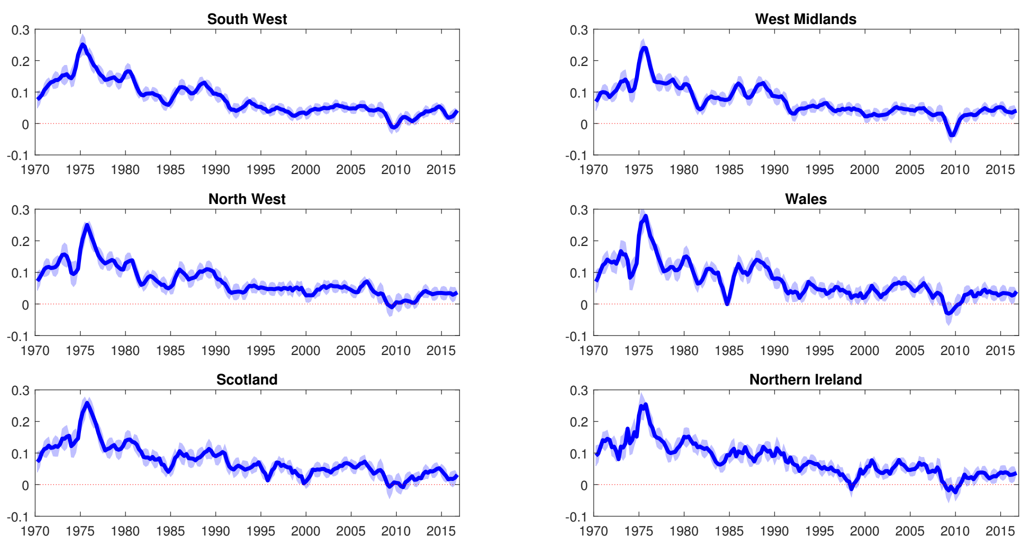


Figure C.4: Regional Nominal GVA Growth Rates: Estimates and Credible Intervals (cont.)

C.4 Results Using A Spatial Prior

Our econometric methods depend heavily on the correlations between variables. For instance, the fact that UK quarterly GVA growth is highly correlated with the regional growth rates, given the cross-sectional restriction, is what infuses our quarterly estimates of the regional growth rates. And GVA growth rates of the different regions are highly correlated with each other. Our MF-VAR allows for these features by allowing the errors in different equations to be correlated (i.e. allowing for static interdependencies between regions). And each region's GVA growth rate depends on lags of other regions' growth rates, thus allowing for dynamic interdependencies between regions. These features are built into our likelihood function. But our prior does not have any such features. The Dirichlet-Laplace prior treats each parameter as being independent of the others. One may wonder if building static or dynamic interdependencies into the prior might improve estimation or forecasting. For this reason (and as a robustness check), we estimated the MF-VAR-SV using a spatial prior. We present results from this prior in this appendix.

We take the spatial prior of LeSage and Krivelyova (1999) which is a prior for the coefficients of the first lag in a VAR, Φ_1. This involves a so-called contiguity matrix which we illustrate with three regions. Each row of the contiguity matrix relates to a region, with non-zero elements denoting the a region itself and its neighbours. Rows are normalised to sum to one. So, for instance, if region 3 is adjacent to the two other regions, but regions 1 and 2 are not adjacent to each other, we would have

$$\mathbf{C} = \begin{bmatrix} \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}. \tag{C.1}$$

The spatial prior is given by:

$$\mathbf{\Phi}_1 \sim N(\mathbf{C}, \mathbf{V}_c). \tag{C.2}$$

We choose a prior covariance matrix of where $\mathbf{V}_c = \begin{bmatrix} \frac{1}{1000} & \frac{1}{1000} & \frac{1}{1000} \\ \frac{1}{1000} & \frac{1}{1000} & \frac{1}{1000} \\ \frac{1}{1000} & \frac{1}{1000} & \frac{1}{1000} \end{bmatrix}$.

For all the other VAR coefficients on longer lags and the error covariance matrix we use the same prior as in the body of the paper.

We will not present a full set of results using this prior since its marginal likelihood is much lower than the one produced using the Dirichlet-Laplace prior. Results for the two priors are very similar and, where they differ, the Dirichlet-Laplace prior is producing the more reasonable results. Table C.8 can be compared to Table 2. They both use exactly the same econometric model and (nominal, final vintage GVA) data set but differ only in the prior.

Table C.8: Connectedness Estimates Using the Spatial Prior, 2016Q4, 1 quarter ahead forecast horizon

	UK	CPI	Bank rate	Ex. rate	Oil price	North East	York. and H.	E. Midlands	E. of England	London	South East	South West	West Midlands	North West	Wales	Scotland	N. Ireland	**From**
UK	68.9%	1.2%	1.4%	0.2%	0.6%	1.6%	0.9%	5.9%	6.1%	3.4%	1.9%	1.5%	0.9%	1.1%	1.1%	0.6%	2.6%	**31.1%**
CPI	1.3%	75.8%	1.3%	0.5%	0.1%	0.1%	0.3%	5.1%	3.4%	1.5%	0.4%	0.4%	0.5%	0.6%	5.2%	1.4%	2.3%	**24.2%**
Bank rate	1.6%	1.3%	79.4%	0.1%	0.1%	0.5%	0.6%	2.8%	5.9%	1.3%	1.3%	0.4%	0.5%	0.8%	1.0%	1.5%	1.0%	**20.6%**
Ex. rate	0.0%	0.1%	0.0%	79.2%	2.6%	1.6%	2.0%	0.5%	0.5%	0.9%	0.9%	1.5%	1.1%	0.9%	4.6%	1.8%	1.7%	**20.8%**
Oil price	0.0%	0.0%	0.0%	0.7%	74.2%	1.2%	0.6%	1.5%	1.7%	2.4%	1.8%	1.3%	1.7%	5.6%	3.1%	2.8%	1.4%	**25.8%**
North East	0.6%	0.0%	0.2%	2.9%	7.4%	74.5%	0.4%	0.9%	1.4%	0.9%	1.0%	0.9%	0.8%	2.0%	2.8%	1.6%	1.5%	**25.5%**
York. and H.	0.4%	0.1%	0.2%	3.6%	4.3%	0.6%	79.0%	0.5%	1.5%	1.1%	0.8%	1.2%	2.1%	1.1%	1.2%	1.2%	1.0%	**21.0%**
E. Midlands	1.7%	1.5%	0.8%	0.9%	7.7%	0.8%	0.4%	63.4%	6.3%	3.6%	1.9%	1.7%	0.9%	2.3%	1.9%	1.4%	2.8%	**36.6%**
E. of England	1.5%	0.8%	1.3%	0.7%	7.4%	1.0%	1.1%	4.8%	63.1%	1.3%	1.3%	1.0%	1.4%	3.6%	5.1%	2.3%	2.2%	**36.9%**
London	0.8%	0.3%	0.3%	1.3%	9.0%	0.7%	0.8%	2.9%	1.4%	72.6%	1.1%	0.8%	1.5%	1.8%	1.6%	1.8%	1.4%	**27.4%**
South East	0.5%	0.1%	0.4%	1.4%	8.9%	1.0%	0.7%	2.0%	1.8%	1.5%	66.1%	0.9%	0.8%	1.7%	1.3%	1.0%	9.8%	**33.9%**
South West	0.4%	0.1%	0.1%	2.3%	7.1%	0.8%	1.1%	1.8%	1.5%	1.2%	1.0%	73.5%	3.1%	2.4%	1.3%	0.7%	1.3%	**26.5%**
West Midlands	0.3%	0.1%	0.1%	1.7%	8.5%	0.7%	1.7%	1.0%	1.7%	2.0%	0.9%	3.0%	71.9%	1.6%	2.2%	1.6%	1.1%	**28.1%**
North West	0.2%	0.1%	0.1%	1.0%	14.9%	1.2%	0.6%	1.5%	2.9%	1.5%	1.1%	1.6%	1.1%	63.4%	6.0%	1.5%	1.3%	**36.6%**
Wales	0.2%	0.8%	0.1%	3.6%	8.5%	1.3%	0.5%	1.0%	3.2%	1.2%	0.7%	0.7%	1.2%	4.7%	69.1%	1.5%	1.7%	**30.9%**
Scotland	0.1%	0.3%	0.3%	2.0%	9.6%	1.1%	0.7%	1.1%	2.1%	1.7%	0.7%	0.5%	1.3%	1.9%	2.1%	73.0%	1.5%	**27.0%**
N. Ireland	0.5%	0.4%	0.2%	1.7%	5.4%	0.9%	0.5%	1.9%	1.9%	1.3%	5.8%	0.9%	0.8%	1.5%	2.3%	1.5%	72.5%	**27.5%**
To	**10.1%**	**7.4%**	**6.9%**	**24.6%**	**102.1%**	**15.2%**	**13.0%**	**35.4%**	**43.5%**	**26.9%**	**22.5%**	**18.4%**	**19.7%**	**33.4%**	**42.7%**	**24.1%**	**34.7%**	**28.3%**

C.5 Scottish Data

In the main body of this article we noted that one part of the UK, Scotland, already has quarterly GVA growth estimates which are produced by the Scottish Government. These data are not as timely as equivalent data for the UK as a whole, but are nevertheless produced within three months of the end of the quarter to which they relate. While these data do not, at the moment, directly enter our model, they do provide an interesting comparison for our model's estimates of regional growth in Scotland (which recall is based on the ONS's estimates of annual real economic growth in Scotland).

Nominal growth estimates for Scotland produced by the ONS and the Scottish Government are very similar; however, because the ONS and the Scottish Government take a different approach to measuring changes in prices in Scotland, the real terms economic growth estimates can differ a little. Essentially, the Scottish Government follow a similar 'bottom up' approach to producing these estimates for Scotland as the ONS does for the UK wide growth data. Meanwhile in producing their regional growth estimates the ONS takes a 'top down' approach based on UK wide sectoral deflators. Figure C.5 below provides this comparison of our model's results (labelled KMMP) to those of the Scottish Government.

Figure C.5: Comparison of our (KMMP) model estimates for Scotland to data produced by the Scottish Government

We can see that our model produces estimates of quarterly economic growth in Scotland which track those of the Scottish Government closely over our evaluation period. This suggests that our model does do a good job of tracking economic growth, on a quarterly basis, in Scotland.