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

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Abstract: Output growth estimates for the regions of the UK are currently published at the annual frequency only, released with a long delay and offer limited historical coverage. To improve the regional database this paper develops a mixed-frequency multivariate model and uses it to produce consistent estimates of quarterly regional output growth dating back to 1970. We describe how these estimates are updated and evaluated on an ongoing, quarterly basis to publish online (at `www.escoe.ac.uk/regionalnowcasting`) more timely regional growth estimates. We illustrate how the new quarterly data can contribute to our historical understanding of business cycle dynamics and connectedness between regions.

Keywords: Regional data; Mixed frequency; Temporal disaggregation; Nowcasting; Bayesian methods; Real-time data; Vector autoregressions

JEL Codes: C32, C53, E37

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1 Introduction

"That's your bloody GDP. Not ours." So famously shouted a Brexit heckler in Newcastle, in the North East of England, 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 East Midlands of England, in the aftermath of the global financial crisis, asking "*whose* recovery were we actually talking about?". He then went on to emphasize the need to "disaggregate" the "economic jigsaw" to provide a more meaningful, including regionally disaggregated, picture of the UK economy (Haldane, 2016).

Many macroeconomic variables at the national (in our application, 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. However, official GVA data for the UK regions are currently only available from the national statistics office, 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.

Similar issues are faced in other countries, as emphasized by Stock (2005): "an important practical challenge facing regional economists is combining ... different sources of data to provide a timely and accurate measure of regional economic activity". For example, in the US the Bureau of Economic Analysis produces their advance US-wide quarterly GDP data about one month after the end of the quarter. However, quarterly state domestic product data exist only from 2005 and are published three months later than GDP data for the US as a whole. The purpose of this paper is to propose a methodology to exploit different data sources to provide more timely and higher frequency regional (or state) level estimates of (official) output growth. We do so via a detailed application to the UK.

Specifically, we 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

[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 some quarterly Regional Short Term Indicator data in 2019.

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

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 to fill some of the same information gaps that this paper seeks to address with the expected publication later in 2019 of quarterly Regional Short Term Indicator data. In addition, some quarterly GVA data already exist for Scotland. In this paper, we will use these Scottish data as a check on our model-based 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 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 (unobserved) quarterly GVA growth for the UK regions is likely correlated with quarterly UK GVA growth (and possibly other quarterly 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 Autoregression (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. We augment the MF-VAR with additional quarterly predictors at both the regional and UK level, as these additional predictors are also 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 popularized 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; such methods let the data decide what restrictions to impose. The existing literature that 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 them to be effective at ensuring

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

[5] Ghysels (2016) offers a detailed discussion of the relationship between the state space approach and other mixed frequency methods. Koop, McIntyre and Mitchell (2019) 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 innovation of the present paper.

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. Section 2 describes our mixed frequency econometric methods. We start, in subsection 2.1, with a brief literature review. Following this in Section 2.2 our MF-VAR with temporal and cross-sectional constraints is described. Subsections 2.3 and 2.4 then respectively consider the Dirichlet-Laplace hierarchical prior for optimal shrinkage and our posterior simulation algorithm. In Section 3, we present our new quarterly regional estimates and summarize 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. 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, are and will be published online each quarter (at `www.escoe.ac.uk/regionalnowcasting`), on receipt of the latest UK data. Section 5 concludes. Online appendices contain supplementary material about the data, econometric methods and empirical results.

2 Mixed-Frequency Econometric Methods

2.1 A Review of the Literature: Motivation for our MF-VAR

The MF-VAR model that we develop draws on a long tradition of measuring economic activity, in general at an aggregate level, at a higher frequency than official statistics. Like the least squares and state space temporal disaggregation methods of Chow and Lin (1971) and Harvey and Pierse (1984), respectively - and subsequent unifications and developments of these two methods to multivariate dynamic contexts[6] - the MF-VAR model seeks to estimate or interpolate the unobserved or missing higher frequency variable(s) of interest. This involves jointly modeling observed lower frequency data on the variable(s) of interest and observed data on higher frequency indicator variables believed to relate to the variable(s) of interest. Consistent with a more recent mixed frequency nowcasting literature this is accomplished by placing the VAR model in state space form; e.g. see Mariano and Murasawa (2010) and Schorfheide and Song (2015). The state equations are given by a VAR at the higher frequency; and the measurement equation relates the observed lower frequency observations to the unobserved higher frequency variables ensuring temporal aggregation is satisfied. In effect, this temporal aggregation constraint ensures that the interpolated higher frequency estimates 'add up' to the observed lower frequency data. The Kalman filter is used to "fill in" the missing higher frequency observations, handling both the mixed frequency and the "ragged-edge" nature of the data.[7]

[6] For example, see Mitchell et al. (2005), Proietti (2006, 2011) and Schorfheide and Song (2015).

[7] "Ragged-edge" means that due to differential publication lags there can be missing values for some variables at the end of the sample.

Alternatives to a VAR, including mixed frequency dynamic factor models with temporal aggregation constraints, have been used in other nowcasting applications; e.g. see Mariano and Murasawa (2003), Bańbura and Rï¿œnstler (2011) and Frale et al. (2011). The Kalman filter again delivers estimates of the missing observations. Foroni and Marcellino (2014) provide a comparison of mixed frequency approaches for nowcasting. We follow studies like Schorfheide and Song (2015) and use the VAR. This choice is also supported by empirical evidence (see, among many others, Carriero, Clark and Marcellino, 2015) that VAR models can be effective forecasting and nowcasting tools in practice.

Related mixed frequency approaches, following Stock and Watson (1989), use dynamic factor models and involve constructing coincident indicators of higher frequency economic activity from a set of higher frequency business cycle indicators; e.g. see Forni et al. (2001). But as argued by Mariano and Murasawa (2003) and Mitchell et al. (2005), an advantage of producing higher frequency estimates of economic activity itself (as measured directly by GDP or GVA, as in this paper), rather than estimates of the underlying "state of the economy" as represented by the estimated common factor, is that this facilitates evaluation of the higher frequency estimates. The higher frequency estimates must relate to and be consistent with the observed lower frequency data. This is captured by the temporal aggregation constraint.

A smaller literature uses variants of these mixed frequency econometric methods to measure specifically regional economic activity at a higher frequency than is provided by the official statistical agencies. Again rather than construct, separately for each region, higher frequency estimates of a latent "economic activity index" (e.g. as Crone and Clayton-Matthews (2005) do for 50 states and Arias et al. (2018) do for 50 metropolitan statistical areas of the US), our focus in the MF-VAR is producing higher frequency estimates of regional GVA itself. Our multi-region focus also means another constraint arises. That is, the regional (or disaggregated) data must be consistent with the observed aggregate (economy-wide) totals. As we explain below in a state space context, this cross-sectional constraint ensures "coherence". But it also provides an important source of higher-frequency conditioning information when nowcasting regional GVA in real-time.[8]

Our MF-VAR model, with the temporal and cross-sectional constraints, can also be interpreted as a flexible and dynamic model-based generalization of Di Fonzo (1990). Di Fonzo (1990) provides a least squares estimator for missing data subject to both temporal and cross-sectional constraints. Cuevas et al. (2015) develop a variant of this matrix based approach, that does not rely on Kalman filtering, to produce higher frequency estimates of regional (chain linked) GDP in Spain.

2.2 The MF-VAR Model and the Cross-sectional Restriction

This section sets out the form of the MF-VAR model that we use to produce the new regional estimates and explains its properties. Further details are in the online Technical Appendix.

We use the following notational conventions, emphasizing that, like Schorfheide and Song (2015) and others, we model output in logarithmic differences:[9]

- $t = 1, .., T$ 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.

[8] Our one-step multivariate model-based approach to imposing "coherence" can be contrasted with least squares approaches that first forecast each disaggregate series independently then, at a second step, impose coherence such that forecasts for the disaggregates add up to forecasts of the aggregated series; e.g. see Wickramasuriya et al. (2019).

[9] In Appendix C.3 we consider the modifications to our MF-VAR required when we model in exact growth rates. We also show that estimation results are similar and not sensitive to the data transformation chosen.

- $y_t^{UK} = log(Y_t^{UK}) - log(Y_{t-1}^{UK})$ is the quarterly growth rate 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. Let $y_t^A = \left(y_t^{1,A}, .., y_t^{R,A}\right)'$ denote 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 growth rate in GVA in region r. It is never observed. Let $y_t^Q = \left(y_t^1, .., y_t^R\right)'$ denote the vector of quarterly GVA growth rates for the R regions.

The MF-VAR is a state space model, comprising a transition equation and a measurement equation. The transition equation of the MF-VAR models the unobserved y_t^Q along with the observed UK quarterly data, y_t^{UK}, using a VAR.[10] Specifically, let $y_t = \left(y_t^{UK}, y_t^{Q\prime}\right)'$ be a $n = R+1$ vector assumed to evolve as:

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

where u_t is i.i.d. $N(0, \Sigma_t)$. The goal of our econometric analysis is to produce posterior and predictive densities for these regional quarterly growth rates, y_t^Q. We use posterior means as point estimates of these growth rates. The posterior is also used to produce credible intervals.

We emphasize that, except for y_t^{UK}, the elements of y_t are not observed. But what we do observe (every fourth quarter, ignoring publication lags for now) is the annual regional growth rate $y_t^{r,A}$, where $y_t^{r,A}$ is the weighted sum of the quarterly latent states y_t^r:

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

Note that (2) is an approximate relationship between the annual and quarterly log differences, as used by Mariano and Murasawa (2003, 2010), Mitchell et al. (2005) and Schorfheide and Song (2015). This approximation preserves the linear structure of the state space model.

We can define a matrix, Λ^A, which imposes the temporal constraint 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:

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

where $z_t = \left(y_t', .., y_{t-6}'\right)'$. The role of M_t^A in (3) is understood if we remember that we only observe $y_t^{r,A}$ 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 as a whole they are simpler, since we observe 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

[10]In our empirical work below, we augment the vector, y_t, with additional observed quarterly data for the UK and include regional quarterly data as exogenous predictors. For ease of exposition, our notation in this section does not include these additional variables.

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 essentially 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 relationship holds:[11]

$$y_t^{UK} = \frac{1}{R} \sum_{r=1}^{R} y_t^r + \eta_t, \tag{5}$$

where $\eta_t \sim N(0, \sigma_{cs}^2)$ captures the approximate nature of this relationship. When $\sigma_{cs}^2 > 0$, UK output need not equal the sum of regional output (in levels). We impose this stochastic constraint using a method developed in Doran (1992). This involves adding (5) as an additional measurement equation to the state space model.[12] The online Appendix B.2 provides details. An additional reason for this cross-sectional relationship to be an approximate one is that the output from the UK continental shelf (UKCS) is not included in the vector of regional outputs, y_t^Q, given its idiosyncratic time-series properties. UKCS mostly reflects oil and gas output from the North Sea.[13] But UKCS is part of the UK GVA figure, y_t^{UK}, as measured by the ONS. This means UK output is not the sum of the R regions' output in levels. Note that it is not possible to remove UKCS activity from the overall estimates of UK quarterly GVA.[14]

Next we need to define 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 worked 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:

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

[11]Note that, as explained in Appendix C.3, if we were to use exact growth rates rather than logarithmic differences, then the (exact) cross-sectional constraint weights each region proportionally to its share of UK GVA. But, when using log differences, Appendix B.2.1 shows that the simple average can be shown to be a first order approximation.

[12]In our posterior simulation algorithm, (5) imposes (stochastically) the constraint for each draw. This means that as $\sigma_{cs}^2 \to 0$ the posterior density for y_t^{UK} approaches the equal-weighted sum of the regional posterior densities. Taeib et al. (2017) call this (density or probabilistic) coherence.

[13]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.

[14]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.

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.

We note that in Koop, McIntyre, Mitchell and Poon (2018), which is the working paper version of the present paper, we presented econometric evidence in support of our MF-VAR-SV. In particular, marginal likelihoods strongly indicated that the homoskedastic version of our model was not supported and that SV is present in our real and nominal data sets. Furthermore, marginal likelihoods also indicated some support for adding additional macroeconomic indicators to the model. Accordingly, in this paper we will only present results from models which include SV and are augmented with additional macroeconomic and regional indicators (as noted below). The reader is referred to our earlier working paper for empirical justification of these choices.

2.3 Dirichlet-Laplace Hierarchical Prior for Optimal Shrinkage

The MF-VAR defined in the previous sub-section is undoubtedly over-parameterized. The VAR embedded in the MF-VAR is quite large (involving, even before we include any additional macroeconomic and regional 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-parameterization 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 is to use these methods with the MF-VAR defined in the preceding sub-section.

As noted in the online Appendix B.1, the state equations for our state space model can be written in multivariate regression form where $\beta = vec([\Phi_0, \Phi_1, \ldots, \Phi_p]')$ is a k dimensional vector of VAR coefficients. We use Dirichlet-Laplace priors (see Bhattacharya et al. 2015) on these coefficients. If we define $\beta = (\beta_1, \ldots, \beta_k)'$, then the prior for each coefficient is independent of the other coefficients and takes the form:

$$\beta_j \sim N(0, \psi_j^\beta \vartheta_{j,\beta}^2 \tau_\beta^2), \tag{9}$$

$$\psi_j^\beta \sim \mathrm{Exp}(\frac{1}{2}), \tag{10}$$

$$\vartheta_{j,\beta} \sim \mathrm{Dir}(\alpha_\beta, \ldots, \alpha_\beta), \tag{11}$$

$$\tau_\beta \sim \mathrm{G}(k\alpha_\beta, \frac{1}{2}). \tag{12}$$

Note that this 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, $\psi_j^\beta \vartheta_{j,\beta}^2 \tau_\beta^2$, determines the degree of shrinkage. Large values of the prior variance imply very little shrinkage is done and the Bayesian estimate is similar to the MLE. However, if the prior variance 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.

The terms making up the prior variance, ψ_j^β, $\vartheta_{j,\beta}^2$ and τ_β^2, are treated as unknown parameters and estimated. Thus, the algorithm automatically decides whether the prior variance for each coefficient should be near zero or not. The Dirichlet-Laplace prior is hierarchical: it is expressed in terms of unknown parameters which in turn require their own priors. It is an example of a global-local shrinkage prior since it involves the prior variance being composed of a term which is local (i.e. ψ_j^β is specific to the j^{th} coefficient) and a term which is global (i.e. τ_β^2 is the same for all coefficients). 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 and is a common feature of a range of variable selection priors such as the Bayesian Lasso (see Park and Casella, 2008). The Dirichlet-Laplace prior adds an extra term, $\vartheta_{j,\beta}^2$. Bhattacharya et al. (2015) prove that the Dirichlet-Laplace prior leads to a posterior which contracts to the true value at a rate which is optimal in a theoretical sense (i.e. the posterior contracts at the minimax rate). This is better than other alternatives such as the Bayesian Lasso.

The Dirichlet-Laplace prior involves only one prior hyperparameter, α_β, making the job of prior elicitation particularly easy. Bhattacharya et al. (2015) recommend setting it to $\frac{1}{2}$ and the results in the body of the paper reflect this. Results using a tighter prior which sets the hyperparameter to $\frac{1}{10}$ are given in Appendix B.1.3 to demonstrate prior robustness.

In addition to undertaking Dirichlet-Laplace shrinkage on the MF-VAR coefficients, we also shrink the coefficients in $\mathbf{a}$ which appear in L; see equation (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. Details on how this is done are given in the online Technical Appendix.

2.4 Posterior Simulation Algorithm for the MF-VAR-SV

Complete details of our posterior simulation algorithms are given in the Technical Appendix. Here we describe the basic structure and intuition of our MCMC algorithm.

Our MCMC algorithm involves various blocks which are drawn from three different branches of the statistical literature. With each of these, the algorithms are familiar, and have been thoroughly tested and found to work well in many applications. These are: i) the state space literature, ii) the literature on hierarchical variable selection priors in general and the Dirichlet-Laplace prior in particular and iii) the literature on stochastic volatility. We discuss each of these in turn.

As emphasized in Schorfheide and Song (2015), the basic MF-VAR is a Normal linear state space model where the goal is to learn about the unobserved latent states. In our case, these are the unobserved quarterly regional GVA growth rates. There is a large Bayesian literature on posterior simulation in Normal linear state space models. Influential early papers include Carter and Kohn

(1994) and Fruhwirth-Schnatter (1994), with Koop and Korobilis (2009) surveying this work. We use the precision sampler of Chan (2017) which is computationally more efficient than methods involving the Kalman filter. This part of our MCMC algorithm is the same as Schorfheide and Song (2015), with the exception of our use of the precision sampler and the addition of the extra measurement equation given in (5).

The blocks of the MCMC algorithm relating to the Dirichlet-Laplace prior are derived in Bhattacharya et al (2015). Kastner and Huber (2017) uses this algorithm in a large VAR. Section 4 and 6.4 of Kastner and Huber (2017) discusses its computational properties. In terms of computation time they note (page 23): "Even though the efficient sampling schemes outlined in this paper help to overcome absolutely prohibitive computational burdens, the CPU time needed to perform fully Bayesian inference in a model of this size can still be considered substantial".

The addition of stochastic volatility implies a nonlinear state space model and, thus, results for Normal linear state space models described above cannot be used to draw the volatilities. However, various Bayesian posterior simulation algorithms for stochastic volatility have been developed. The auxiliary mixture sampler of Kim et al. (1998) has been found to work particularly well. In this paper, we follow Chan and Eisenstat (2018) and use the algorithm of Kim et al. (1998) in conjunction with the precision sampler.

3 Empirical Results: Quarterly Regional Growth Estimates

3.1 Annual Regional and Quarterly Macroeconomic and Regional 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 modeling real-time data given data revisions, we have constructed two versions of the nominal GVA data set: a latest vintage[15] and a real-time one. When producing historical estimates of quarterly regional growth rates, we use the latest vintage. We also 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 source, which is used to construct data from 1998 onwards, but was published by ONS for the first time in December 2017, comprises 'balanced' estimates of regional GVA (referred to as GVA(B) by ONS). Balancing involves reconciling the income and production based estimates of GVA (see Fenton (2018) for details); the latest data cover the period 1998 to 2018. Secondly, pre-1998 real regional data are obtained by deflating the available nominal regional GVA data using the UK deflator. Thus, the real

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

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, the MF-VAR-SV model, (1), can be used to produce quarterly regional growth rate estimates for these 12 regions of the UK. An MF-VAR-SV using only GVA, $\left(y_t^{UK}, y_t^{Q\prime}\right)'$, would be a 13-dimensional model. 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. We emphasize that these quarterly GDP data, for the UK as a whole, are published with a much shorter lag than the regional data.

But it is possible that other quarterly macroeconomic series, in addition to y_t^{UK}, might be expected to provide helpful indications of quarterly regional growth. Hence, 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-SV. 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.[16]

Following Cuevas et al. (2015), we also add quarterly regional indicator data into the model. Relevant regional data going back to 1966 are difficult to find. As described in the online Data Appendix, we have constructed a measure of regional unemployment and business optimism on a regional basis going back to 1966. The former is based on the monthly claimant count rate measure of unemployment (although we choose to work with these data aggregated to the quarterly frequency), and the latter uses the Confederation of British Industry's (CBI) Business Optimism Survey, produced on a quarterly basis. The inclusion of these two higher frequency variables, with importantly both published on a timely basis relative to regional GVA (see Figure 6 below), may help capture idiosyncratic movements in (interpolated) quarterly regional GVA. Both indicators are included in the VAR as region-specific exogenous variables (i.e. the equation for region i will include the regional quarterly data only for region i). Thus, the results in this paper use a 17 dimensional MF-VAR-SV where each equation contains these two exogenous variables. Results using smaller specifications, without these regional quarterly variables or without the additional UK macroeconomic variables, are provided in the working paper version of this paper; see Koop, McIntyre, Mitchell and Poon (2018). The working paper also provides evidence that including the additional UK quarterly variables (instead of working with a 13-dimensional model involving only GVA data) is empirically warranted. Similarly, to be consistent with the number of lags in the inter-temporal restriction in (2), we choose a lag length of $p = 7$ and marginal likelihoods indicate support for this choice. 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.

3.2 Historical Estimates of Quarterly Regional Growth

We estimate our MF-VAR-SV models on the latest (or *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 use our model to update these estimates in real-time (each quarter) and they are available at `www.escoe.ac.uk/regionalnowcasting`.

Figure 1 presents the nominal and real estimates alongside the UK growth rate from 1970. To

[16]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.

aid in comparability with the published annual regional data, our quarterly estimates are annualized (i.e. we take our quarterly regional GVA estimates and construct an annual change using (2)).

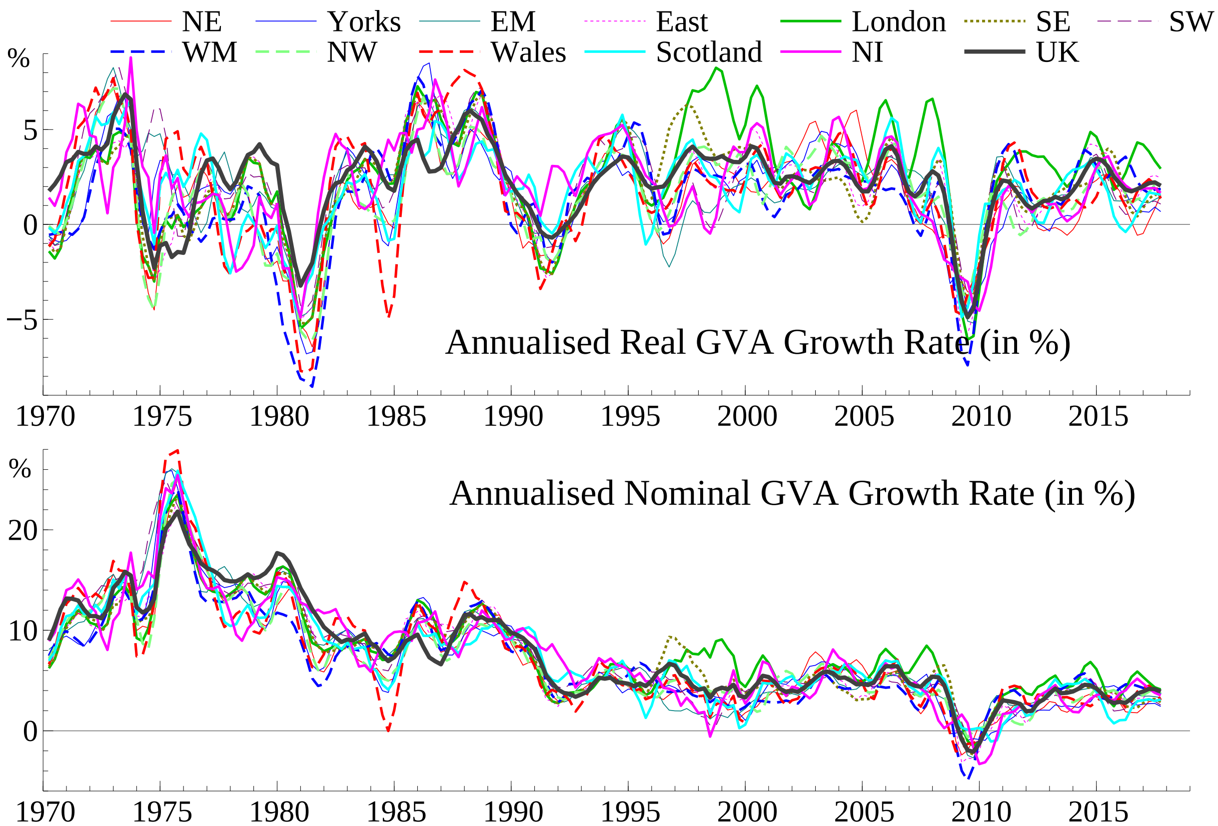


Figure 1: Historical Estimates of Regional GVA Growth

Section 4 below illustrates how use of our new data can enrich our understanding of the UK economy. Before this we draw out five 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 equation (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, in the same units as Figure 1, the estimate of the error in the measurement equation, (2), along with a credible interval for the nominal estimates (similar estimates are found for real GVA). 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.

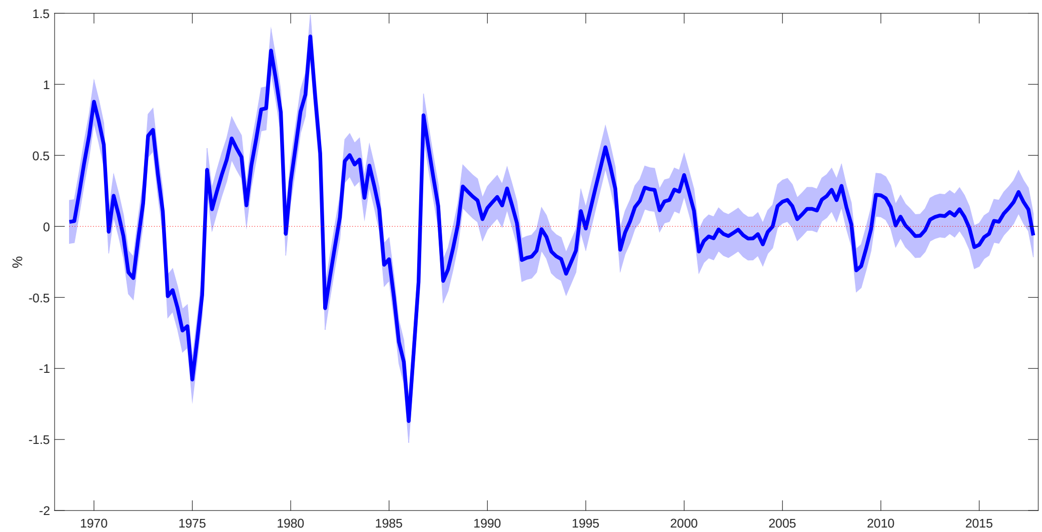


Figure 2: Errors in Cross-sectional Restriction using Using Nominal GVA (68 percent credible interval is shaded)

Secondly, inspection of the 68 percent credible intervals around our regional nominal and real GVA growth estimates (see Appendix C.2) shows that our regional estimates are quite precise. Since we plot annualized 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 neighboring 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 this paper use this prior. Results using the spatial prior are included in the working paper version of this paper (Koop, McIntyre, Mitchell and Poon (2018)) along with complete details of the spatial prior.

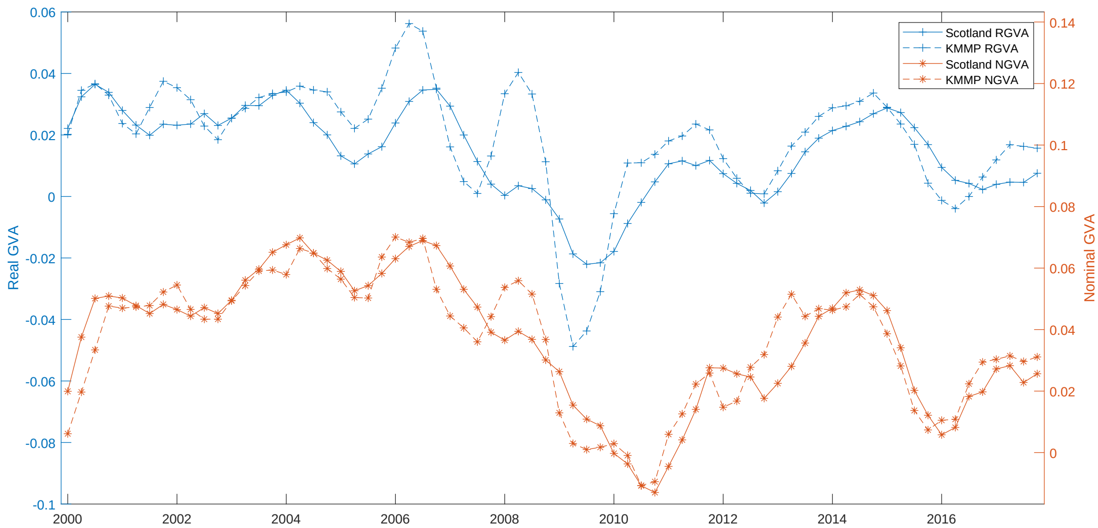
Fourth, we re-estimated the MF-VAR-SV using data in exact growth rates (instead of log differences) and found results to be very similar. Details are provided in Appendix C.3

Fifth, as another 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 nominal and real GVA estimates from 1997Q1. The Scottish 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 directly enter our model, they can be used as a check on our methods. Although we should stress that the ONS and Scottish Government estimates for real 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 goes the other way and construct their deflators for Scotland just like the ONS does for the UK as a whole. This includes the use of direct volume estimates for some sectors[17]. Nevertheless, it would

[17] For more detail of the construction of the Scottish real–terms GDP series, see: `https://www2.gov.scot/Resource/`

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 3 shows, our estimates do track those from the Scottish Government quite well, with a correlation coefficient against the Scottish data of 0.91 for nominal GVA and 0.78 for real GVA.[18]

Figure 3: Comparison of Our (KMMP) Estimates To Scottish Government's: Nominal and Real GVA Growth (4Q–on–4Q) in %



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 analyze 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

0054/00548041.pdf

[18]We use December 2017 vintage data from the Scottish Government to match the *final* or latest vintage data, from the ONS, that we use for the UK and its regions.

GVA since recessions are typically defined in terms of real quantities.[19] This algorithm identifies four main recessions for the UK as a whole. These start in 1973Q3 (continuing in 1974), 1979Q3, 1990Q3 and 2008Q2.[20]

Figure 4 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 lackluster 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 West Midlands 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.

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 characterized by 34 regional recessions, four of which were in each of the devolved nations (Northern Ireland, Scotland and Wales) 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, around 30 quarters in expansionary phases of the business cycle, 9 of the 12 regions (all except London, the South East and the East Midlands) spent less than half this time in an expansion. The amplitude of these expansions 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 and the South East having concordance estimates of 91% and

[19] 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 Figures C1 to C4, in the online Empirical Appendix, show that the credible intervals around the central regional growth estimates are quite precise. While there are differences, a qualitatively similar picture to that found below also emerges when we analyze 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, may be 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.

[20] These dates mostly accord with the views of others. For instance, 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 formalize 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.

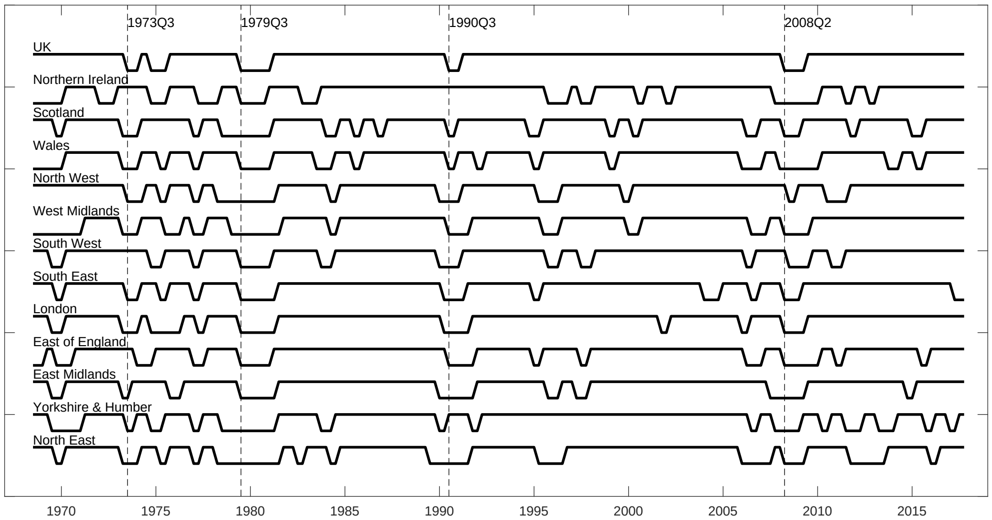


Figure 4: Start and End Dates of Regional and UK Recessions Using Quarterly Real GVA

89%, respectively; with the North East and Yorkshire and the Humber having lower estimates of 76% and 77%, respectively. The East and West Midlands are in the middle, as their names suggest, with estimates of 85% and 80%, respectively. Of the devolved nations, Northern Ireland again stands out as the most idiosyncratic with the lowest (joint with the North East) concordance estimate of 76%; and Scotland and Wales both having estimates of 81%, 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 analyzing and understanding the transmission of shocks and business cycle dynamics, Figure 5 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, the North West, Yorkshire and the Humber and Wales 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 3.2 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 5, 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 emphasize the stop-start nature of the economic recoveries of many of the regions, in particular Northern Ireland, after the 1979 and 2008 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

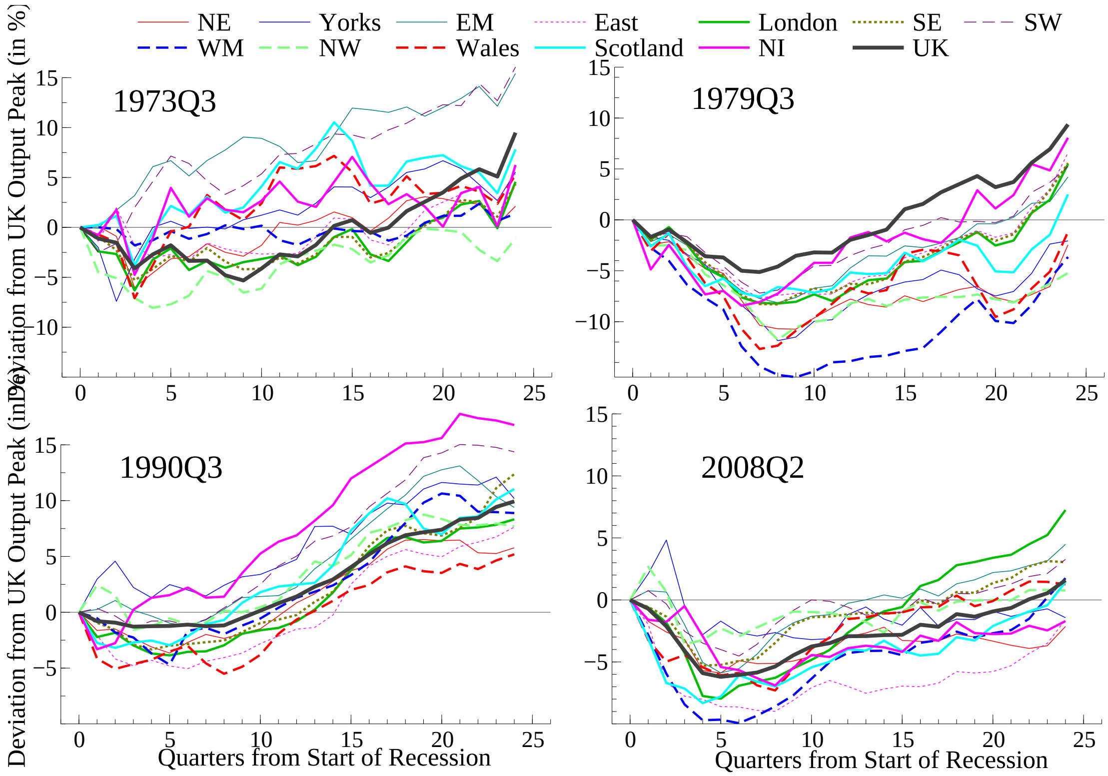


Figure 5: The Regional Profiles of Four UK Recessions

developed in Diebold and Yilmaz (2014).

Connectedness measures can be defined based on any variance decomposition. We use the generalized variance decomposition developed in Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) which 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 $d^h_{i,j}$ 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. Section 3 of Pesaran and Shin (1998) discusses the properties of the generalized variance decomposition and the relationship with the orthogonalized variance decompositions. The latter are usually identified using an ordering of the variables in the VAR. But, in our application, no logical ordering of the variables suggests itself and, hence, we avoid use of orthogonalized variance decompositions.

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 $d^h_{i,j}$ 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:

$$\text{Connectedness } \textbf{from}\text{: } \sum_{j \neq i} d^h_{i,j} \tag{13}$$

Table 1: Properties of Regional Contractions and Expansions

	Durations (quarters)		Amplitude (quarters)		Concordance
	Contractions	Expansions	Contractions	Expansions	
North East	5.00	10.17	-0.03	0.09	76%
Yorkshire and The Humber	3.67	9.79	-0.03	0.09	77%
East Midlands	4.44	17.88	-0.03	0.15	85%
East of England	4.00	13.00	-0.03	0.11	83%
London	4.33	15.13	-0.04	0.17	91%
South East	3.40	15.60	-0.03	0.13	89%
South West	3.55	12.90	-0.02	0.12	86%
West Midlands	4.60	10.80	-0.05	0.10	80%
North West	4.20	12.33	-0.04	0.10	85%
Wales	3.43	9.57	-0.04	0.10	81%
Scotland	3.13	9.79	-0.04	0.10	81%
Northern Ireland	4.08	10.25	-0.03	0.11	76%
UK	4.40	30.50	-0.04	0.23	100%

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:

$$\text{Connectedness } \mathbf{to}\text{: } \sum_{i \neq j} d_{i,j}^{h} \tag{14}$$

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 emphasize 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 a 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.[21] As shown in online Appendix C.1 the pattern of connectedness is similar when we consider the real data, so we do not discuss it separately. The estimates in Tables 2 and 3 are posterior means at the end of our sample (2017Q4). In Appendix C.1 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. The online appendix also presents

[21] 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 normalize them so they do sum to one. To be specific, in the connectedness tables the percentages sum to 100 across rows (but not down columns).

results for $h = 4$ which lie between the $h = 1$ and $h = 20$ results, but suggest that region-specific effects die out quite quickly.

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 80% of short-run regional growth dynamics. 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 only slightly across regions. But the *connectedness to* measures vary more. For these, Wales and Northern Ireland exhibit higher numbers than the other regions indicating that these regions have the strongest effects on the others.

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 also 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 regional GVA growth. Following Pesaran (2016), the impact of UK GVA growth – given that it is a cross sectional average – might be interpreted as revealing the effects of the common 'factor' driving regional growth dynamics.

Table 3 contains the connectedness measures for $h = 20$ and paints a very different picture. It indicates that the inter-connections between regions are much higher at this longer forecast horizon. Across regions, the idiosyncratic or region-specific shocks typically now explain less than 10%, rather than 80%, of short-run regional growth dynamics. This finding is also supported by evidence from Tables 2 and 3 that UK GVA growth - the common 'factor' driving regional growth dynamics - becomes much more important in explaining regional growth dynamics in the longer run.

Thus, we are finding evidence that an appreciable amount of time is required for growth in one region to spill over to another such that regional growth dynamics share common features. But inspection of results (in the online appendix) reveals that these region-specific shocks explain about 25% to 30% of regional growth dynamics at $h = 4$, suggesting that shocks do begin to spill over across regions quite quickly (within a year) even if it takes considerably longer for this process to complete.

The previous connectedness results were for a particular time period: 2017Q4. In theory, the presence of time-varying volatilities in our model implies that they can change over time, as in Korobilis and Yilmaz (2018). In practice, we find little evidence of changes in connectedness over time. In the working paper version of this paper (Koop, McIntyre, Mitchell and Poon (2018)) we highlighted a few cases where there did appear to be some (albeit modest) changes in connectedness over time. The interested reader can refer to this working paper for further details.

4.3 Nowcasts of Quarterly Regional Growth

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

4.3.1 Design of Nowcasting Exercise

The nowcast evaluation period begins in 2000 and ends with the latest (as of the time of writing) regional estimates for 2017 (published in December 2018). All nowcasts are produced recursively (i.e. produced using an expanding window of data) and involve re-estimation of the VAR models.

Table 2: Connectedness Estimates for 2017Q4, 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	82.2%	1.9%	1.9%	0.7%	1.0%	0.8%	0.7%	1.4%	1.1%	0.9%	1.6%	1.4%	0.9%	0.9%	0.8%	0.6%	1.4%	**17.8%**
CPI	1.7%	83.3%	1.1%	0.8%	0.7%	0.5%	0.7%	1.8%	1.4%	0.9%	0.7%	0.7%	0.9%	0.8%	1.7%	1.1%	1.2%	**16.7%**
Bank rate	1.6%	1.1%	83.1%	0.7%	0.7%	0.9%	0.9%	1.3%	1.9%	1.1%	1.1%	0.9%	0.7%	0.9%	1.0%	1.2%	1.0%	**16.9%**
Ex. rate	0.5%	0.6%	0.5%	82.4%	2.6%	1.2%	1.1%	0.8%	0.7%	1.1%	1.1%	1.1%	1.1%	0.9%	2.0%	1.2%	1.1%	**17.6%**
Oil price	0.6%	0.5%	0.4%	2.2%	82.8%	0.9%	0.7%	1.0%	1.3%	1.2%	1.0%	0.9%	1.0%	2.0%	1.3%	1.1%	1.0%	**17.2%**
North East	0.5%	0.3%	0.6%	1.1%	1.0%	83.1%	0.7%	1.1%	1.2%	1.0%	1.1%	1.1%	1.0%	1.2%	2.2%	1.4%	1.3%	**16.9%**
York and H.	0.4%	0.5%	0.6%	1.0%	0.8%	0.8%	83.6%	1.0%	1.0%	1.3%	1.3%	1.5%	1.3%	1.1%	1.2%	1.2%	1.4%	**16.4%**
E. Midlands	0.7%	1.0%	0.8%	0.7%	1.0%	1.1%	1.0%	79.4%	2.5%	1.8%	1.4%	1.4%	1.1%	1.8%	1.4%	1.3%	1.7%	**20.6%**
E. of England	0.6%	0.8%	1.0%	0.6%	1.1%	1.1%	0.9%	2.3%	80.0%	1.2%	1.3%	1.2%	1.4%	1.4%	2.2%	1.5%	1.4%	**20.0%**
London	0.4%	0.5%	0.6%	0.8%	1.0%	1.0%	1.1%	1.7%	1.3%	83.0%	1.1%	0.9%	1.4%	1.3%	1.3%	1.3%	1.2%	**17.0%**
South East	0.8%	0.4%	0.6%	0.8%	0.9%	1.0%	1.1%	1.3%	1.4%	1.2%	82.1%	1.2%	1.1%	1.1%	1.2%	1.0%	2.8%	**17.9%**
South West	0.7%	0.4%	0.5%	0.9%	0.8%	1.0%	1.3%	1.4%	1.3%	1.0%	1.3%	82.9%	1.8%	1.4%	1.1%	1.0%	1.3%	**17.1%**
W. Midlands	0.4%	0.5%	0.4%	0.8%	0.9%	0.9%	1.2%	1.0%	1.5%	1.5%	1.2%	1.7%	82.5%	1.4%	1.6%	1.3%	1.2%	**17.5%**
North West	0.4%	0.4%	0.5%	0.6%	1.5%	1.0%	0.8%	1.5%	1.3%	1.2%	1.0%	1.2%	1.3%	83.0%	1.9%	1.3%	1.3%	**17.0%**
Wales	0.3%	0.7%	0.5%	1.2%	0.9%	1.5%	0.8%	1.1%	1.8%	1.1%	1.0%	0.9%	1.4%	1.8%	81.0%	1.2%	2.8%	**19.0%**
Scotland	0.3%	0.5%	0.6%	0.8%	0.8%	1.1%	0.9%	1.2%	1.4%	1.2%	0.9%	0.9%	1.2%	1.4%	1.5%	81.8%	3.7%	**18.2%**
N. Ireland	0.5%	0.5%	0.4%	0.6%	0.7%	0.9%	0.9%	1.3%	1.2%	1.0%	2.1%	1.0%	1.0%	1.2%	2.6%	3.1%	80.6%	**19.4%**
To	**10.4%**	**10.5%**	**11.0%**	**14.5%**	**16.6%**	**15.6%**	**15.0%**	**21.3%**	**22.1%**	**18.6%**	**19.2%**	**17.9%**	**18.6%**	**20.5%**	**25.0%**	**20.8%**	**25.8%**	**17.8%**

Table 3: Connectedness Estimates for 2017Q4, 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	10.4%	3.4%	2.8%	2.2%	2.6%	5.6%	5.7%	6.7%	10.2%	5.3%	6.5%	6.8%	6.7%	8.5%	5.3%	5.8%	5.7%	**89.6%**
CPI	9.4%	5.8%	3.4%	2.8%	2.9%	5.4%	5.5%	6.5%	10.0%	5.0%	6.1%	6.8%	6.4%	8.2%	5.0%	5.5%	5.5%	**94.2%**
Bank Rate	9.4%	4.6%	4.8%	2.8%	2.9%	5.5%	5.4%	6.3%	10.0%	5.0%	6.2%	6.4%	6.5%	8.1%	5.1%	5.5%	5.5%	**95.2%**
Ex. rate	8.8%	3.3%	2.7%	2.5%	2.5%	5.7%	5.9%	6.6%	10.3%	5.4%	6.6%	6.6%	7.5%	8.5%	5.4%	5.8%	5.7%	**97.5%**
Oil price	8.8%	3.0%	2.6%	2.0%	2.5%	5.8%	6.0%	6.7%	10.9%	5.4%	6.8%	6.7%	6.9%	8.9%	5.4%	5.9%	5.8%	**97.5%**
North East	8.8%	3.0%	2.5%	1.9%	2.4%	6.4%	5.9%	6.8%	10.4%	5.4%	6.8%	6.8%	7.0%	8.8%	5.4%	5.9%	5.8%	**93.6%**
York. and H.	8.9%	3.0%	2.6%	2.0%	2.4%	5.7%	6.5%	6.8%	10.4%	5.4%	6.7%	6.9%	6.9%	8.7%	5.4%	5.9%	5.8%	**93.5%**
E. Midlands	8.9%	3.1%	2.6%	2.1%	2.5%	5.7%	5.9%	7.4%	10.4%	5.4%	6.7%	6.9%	6.9%	8.7%	5.4%	5.8%	5.7%	**92.6%**
E. of England	8.8%	2.8%	2.4%	1.8%	2.3%	5.7%	6.0%	6.9%	11.1%	5.5%	7.0%	6.9%	7.0%	8.8%	5.4%	6.0%	5.8%	**88.9%**
London	8.8%	3.0%	2.5%	1.9%	2.4%	5.7%	6.0%	6.8%	10.4%	6.0%	6.8%	6.9%	7.0%	8.7%	5.4%	5.9%	5.8%	**94.0%**
South East	8.9%	2.9%	2.5%	1.9%	2.4%	5.7%	6.0%	6.8%	10.4%	5.4%	7.5%	6.8%	7.0%	8.7%	5.4%	5.9%	5.8%	**92.5%**
South West	8.9%	3.0%	2.6%	2.0%	2.5%	5.7%	6.0%	6.8%	10.4%	5.4%	6.7%	7.6%	6.9%	8.6%	5.4%	5.9%	5.8%	**92.4%**
W. Midlands	8.9%	3.1%	2.6%	2.0%	2.5%	5.7%	5.9%	6.8%	10.4%	5.3%	6.6%	6.8%	7.9%	8.6%	5.4%	5.8%	5.7%	**92.1%**
North West	8.8%	2.9%	2.5%	1.9%	2.4%	5.7%	6.0%	6.7%	10.4%	5.4%	6.8%	6.8%	7.0%	9.7%	5.4%	5.9%	5.8%	**90.3%**
Wales	8.8%	2.9%	2.5%	1.9%	2.3%	5.8%	6.0%	6.8%	10.5%	5.4%	6.8%	6.8%	7.0%	8.7%	6.0%	6.0%	5.9%	**94.0%**
Scotland	8.7%	2.8%	2.4%	1.9%	2.3%	5.8%	6.1%	6.8%	10.3%	5.5%	6.8%	6.9%	7.1%	8.7%	5.5%	6.6%	5.9%	**93.4%**
N. Ireland	8.7%	2.8%	2.4%	1.8%	2.3%	5.8%	6.0%	6.9%	10.3%	5.4%	6.9%	6.9%	7.1%	8.8%	5.5%	6.0%	6.4%	**93.6%**
To	**142.4%**	**49.5%**	**41.5%**	**33.0%**	**39.4%**	**90.8%**	**94.3%**	**107.7%**	**165.5%**	**85.6%**	**106.7%**	**108.7%**	**110.8%**	**138.0%**	**85.8%**	**93.5%**	**91.9%**	**93.2%**

Given that real GVA data at the regional level have only been released since 2013 we confine this nowcasting exercise to the nominal data; i.e., we focus on the timely production and evaluation of quarterly nowcasts for nominal regional GVA growth only.

Using our model we produce timely and higher-frequency nowcasts 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 nowcasts 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 nowcasts 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 nowcasts 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 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 and regional indicator variables included in our model, including for the reference quarter. But the ONS publish their estimates for annual regional GVA in the fourth quarter of each year. Thus, it is only (late) in Q4 of each year that we can update our regional nowcasts 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.

For clarity, a release calendar is presented in Figure 6. This illustrates, when nowcasting 2016, the publication dates for UK quarterly GVA data and the regional annual GVA data. For ease of reading, the publication dates for the "other" quarterly economic indicators included in our VAR model are subsumed into one. While the financial market data (the Bank Rate, USD:GBP exchange rate and oil price) are available sooner, like the CPI, claimant count and CBI business optimism data their values are known one month after the end of the reference quarter.

This release calendar is helpful in understanding the timing of our nowcasts. As new information accumulates we produce seven nowcasts of the same fixed-event: annual regional GVA growth ending in a given year, τ. To illustrate, for τ equal to 2016 these seven forecasts would be made quarterly from May 2016, with the last estimate produced in November 2017 in advance of the regional data for 2016 being released the next month. More generally, in our real–time nowcasting exercise we estimate annual regional GVA growth ending in year τ, with τ running from 2000 to 2017. The seven nowcasts for each year (with the timing advantage relative to the ONS's release of year τ regional data given in brackets) are made in: Q2 of year τ (19 months); Q3 of year τ (16 months); Q4 of year τ (13 months); Q1 of year $\tau+1$ (10 months); Q2 of year; $\tau+1$ (7 months); Q3 of year $\tau+1$ (4 months); and Q4 of year $\tau+1$ (1 month).

Having explained the schedule behind the sets of seven nowcasts, we now explain precisely how the MF-VAR-SV can be used to produce them. We stress that we are always producing nowcasts of annual growth rates since we wish to evaluate them against the actual annual data subsequently produced by the ONS. Thus, we take the quarterly nowcasts/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 nowcasts made in Q2 of year τ are constructed from an MF-VAR-SV estimated on a dataset that contains quarterly UK and regional economic data up to and including Q1 of year τ and annual regional data up to year $\tau-2$. This model produces forecasts of quarterly regional growth rates for years τ and $\tau-1$ which are then averaged using (2) to produce an annual nowcast/forecast for year τ.

The forecasts made in Q3 and Q4 of year τ then work with MF-VAR-SVs that use the same regional data as the Q2 model, but the quarterly UK and regional indicators now run through Q2

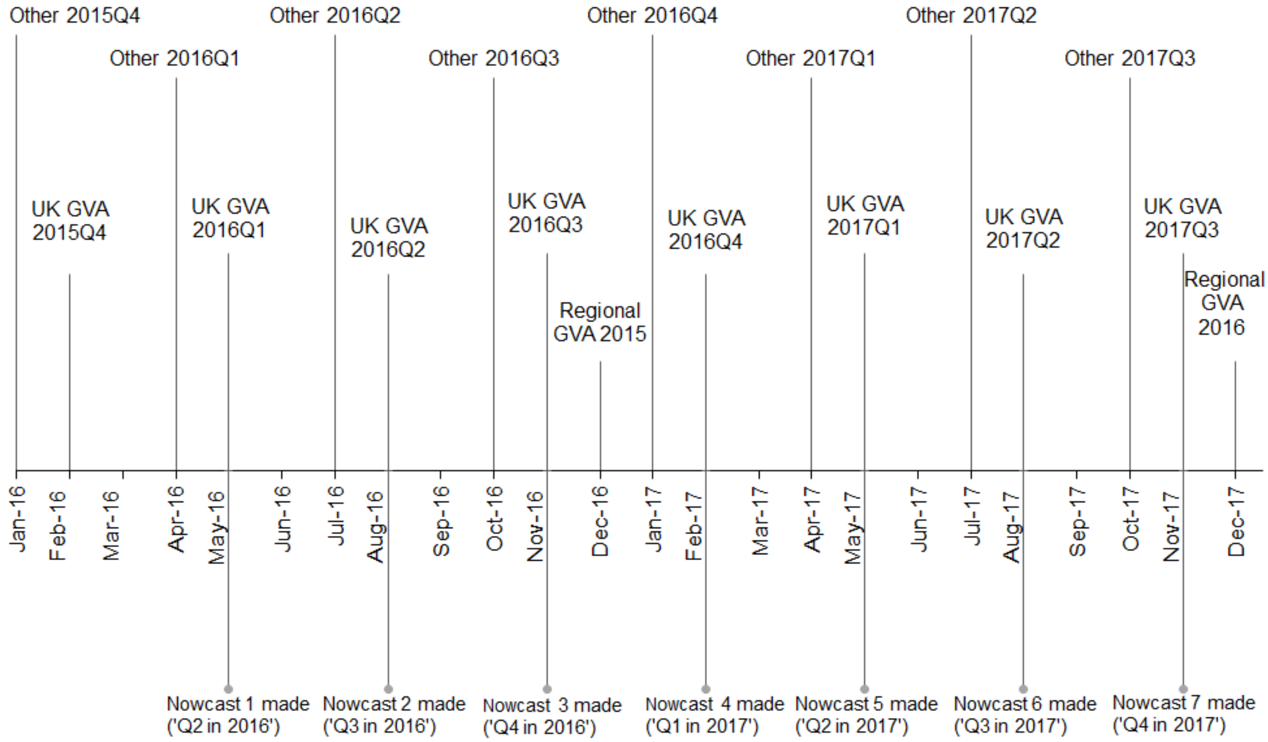


Figure 6: Illustrative data release calendar, indicating the month in which the quarterly and annual data are published, when nowcasting $\tau = 2016$. "Other" refers to the quarterly economic indicators (the Bank Rate, USD:GBP exchange rate, oil price, CPI inflation, the claimant count and CBI business optimism)

and Q3 of year τ, respectively. It is only by the nowcast made in Q1 of year $\tau + 1$ 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 for year τ made in Q1 of year $\tau + 1$ is also the first nowcast we make that is conditional on data for UK GVA growth for all of year τ. Subsequent nowcasts of regional growth in year τ will additionally contain UK and regional 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. ONS finally publish their own estimates for year τ regional GVA at the end of Q4 of $\tau + 1$, after our seventh and final nowcast made in November.

4.3.2 Results of Nowcasting Exercise

We use root mean square forecast errors (RMSFEs) as a measure of the quality of the seven sets of point (conditional mean) nowcasts. To evaluate the quality of the predictive densities we use log scores (sums of log predictive likelihoods). To provide an indication of the size of the benefits of conditioning the regional nowcasts on within-year data and of exploiting inter-regional dynamics, we also present results from two simple benchmarks which lack these features. The first benchmark forecasts annual regional GVA growth using individual AR(1) models for each region. The second uses a VAR(1) on the annual data, and therefore allows for regional dependencies. In both cases, as we progress through the evaluation period, the latest vintage of GVA data are used as indicated in Figure 6. For these benchmarks, estimation and forecasting is carried out using non-informative prior Bayesian methods (i.e. ordinary least squares).[22]

Tables 4 and 5 contain the log scores and RMSFEs, respectively, for our nowcast/forecast comparison exercise. Note first that all of the seven differently timed nowcasts from the MF-VARs are, with some exceptions, more accurate than forecasts from the benchmarks. This is true regardless of region and is particularly strong when using log scores as the measure of forecast performance. The VAR(1) benchmark is especially poor when looking at log scores. These gains over both benchmarks offer strong additional reassurance that mixed frequency and multivariate methods are of great use when density forecasting with our data set. A second point worth noting is that we see a general tendency for forecast accuracy to increase as we move through the year and we accumulate information on the performance of the UK economy with each subsequent estimation. With some exceptions, particularly large improvements are to be found with the receipt in Q1 of year $\tau + 1$ of data about the UK economy in Q4 of year τ. This is reassuring, given that it is when we have these data that we also gain the regional data for year $\tau - 1$. Thus, the evidence suggests that clear accuracy gains are to be had if we wait for publication of both year $\tau - 1$'s regional data and four quarters of year τ UK data before computing our regional nowcasts using our MF-VAR-SV models. This means we can produce good estimates of regional growth in year τ to the same approximate timescale as growth estimates for year τ for the UK as a whole are published by the ONS – this is nearly one year before official data for these regions are released by ONS.

Overall, our nowcasting results suggest that, especially shortly after the end of the year of interest, the econometric methodology developed in this paper can be used to provide reliable and timely nowcasts of regional GVA growth at a higher frequency (indeed a similar frequency to the release of national GDP for the same period) than is possible with conventional methods. In addition to providing more timely indicators of regional growth, this serves as a reassuring (out-of-sample) check on the quality of the regional growth estimates produced in this paper.

5 Conclusions

Regional (or state-level) data measuring economic activity are often less timely, offer less historical coverage and available at a lower frequency than the aggregate (economy-wide) output data provided by the same national statistics office. This is the case in many countries. In general terms this paper considers how regional and country-wide data, often measured at different frequencies, can be brought together to provide more timely and higher frequency regional data.

Specifically, via a detailed application to the UK, this paper's motivation is that economists studying the regions of the UK have historically had to work with such 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 to 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 (discussed by Bean, 2007). We hope the output of this paper - a quarterly regional database for the UK 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.

[22] We also investigated the significance of forecast improvements relative to the benchmarks using the Diebold-Mariano test of equal predictability. When using log-scores, the hypothesis of equal predictability was always rejected in favor of our approach when using the VAR as a benchmark. When using the AR benchmark, we consistently find significant improvements for Q4 of year τ and all later periods. When using RMSFEs, we do not reject the hypothesis of equal predictability relative to either benchmark.

Table 4: Cumulative Log Scores for Nominal GVA Growth Nowcasts, 2000-2017

Nowcast made in:	North East	York. and H	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland
1. Q2 in year τ	27.31	25.85	23.53	23.12	20.94	23.64	22.95	25.76	25.83	23.79	25.30	19.43
2. Q3 in year τ	29.78	28.43	25.33	25.08	21.90	25.46	25.04	27.73	28.62	26.00	27.85	21.86
3. Q4 in year τ	31.28	30.23	26.55	26.54	22.46	26.38	26.72	29.13	29.97	27.55	29.72	23.30
4. Q1 in year $\tau+1$	32.86	32.41	27.68	26.35	23.41	26.45	27.47	30.39	32.09	29.61	31.56	24.27
5. Q2 in year $\tau+1$	33.32	33.63	29.11	26.33	23.79	26.67	28.63	30.78	31.93	29.58	32.00	24.72
6. Q3 in year $\tau+1$	33.15	34.61	30.97	27.19	24.02	27.46	30.58	31.85	31.37	30.10	32.47	26.72
7. Q4 in year $\tau+1$	33.29	35.15	32.20	28.69	24.98	29.11	32.96	32.95	31.76	31.09	32.91	27.24
AR(1) (Non-informative)	26.14	25.85	24.74	21.53	21.61	23.94	24.11	26.65	26.07	25.59	26.30	22.21
VAR(1) (Non-informative)	8.00	9.41	4.03	3.13	1.31	2.04	3.34	-2.22	-4.41	-5.39	-8.29	-11.11

Table 5: RMSFEs for Nominal GVA Growth Nowcasts, 2000-2017

Nowcast made in:	North East	York. and H	E. Midlands	E. of England	London	South East	South West	W. Midlands	North West	Wales	Scotland	N. Ireland
1. Q2 in year τ	0.033	0.033	0.044	0.047	0.054	0.043	0.043	0.039	0.033	0.037	0.032	0.057
2. Q3 in year τ	0.032	0.033	0.046	0.046	0.056	0.046	0.047	0.038	0.029	0.038	0.031	0.053
3. Q4 in year τ	0.033	0.034	0.047	0.046	0.057	0.048	0.047	0.037	0.031	0.038	0.031	0.054
4. Q1 in year $\tau+1$	0.031	0.031	0.046	0.050	0.055	0.050	0.048	0.037	0.027	0.036	0.029	0.055
5. Q2 in year $\tau+1$	0.030	0.027	0.043	0.050	0.055	0.050	0.044	0.036	0.029	0.037	0.028	0.054
6. Q3 in year $\tau+1$	0.030	0.021	0.035	0.046	0.053	0.046	0.038	0.032	0.031	0.034	0.024	0.042
7. Q4 in year $\tau+1$	0.029	0.019	0.031	0.039	0.048	0.038	0.026	0.027	0.029	0.027	0.021	0.039
AR(1) (Non-informative)	0.035	0.034	0.049	0.065	0.064	0.051	0.044	0.037	0.034	0.034	0.038	0.050
VAR(1) (Non-informative)	0.035	0.035	0.068	0.087	0.088	0.054	0.072	0.043	0.044	0.050	0.046	0.086

To do this, we have developed a mixed frequency VAR that allows information from quarterly frequency (and more timely) UK GVA and other indicator 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. We hope that the methodology we propose will be useful in applications beyond the UK that seek to improve the regional database.

Given that it is anticipated that 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 into our model. These data will be available for only part of our sample but, we hope, will provide a source for improving, validating and testing our quarterly nowcasts ('flash estimates') of quarterly regional GVA published at `www.escoe.ac.uk/regionalnowcasting`. They will also ensure that our model-based estimates remain consistent with ONS data and ongoing improvements to these. Given that these new quarterly regional data from the ONS will be published with a delay of 3 to 4 months, our quarterly nowcasts will continue to provide an earlier indication of regional economic activity.

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Online Appendix for "Regional Output Growth in the United Kingdom: More Timely and Higher Frequency Estimates From 1970" by Gary Koop, Stuart McIntyre, James Mitchell and Aubrey Poon

In this set of three appendices, we describe the data (A. Data Appendix), provide full details of our econometric methods (B. Technical Appendix) and present some supplementary empirical results (C. Empirical Appendix).

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 2017 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 utilize the ONS's balanced GVA data, GBA(B), for the period 1998-2017[23]; 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; and regional indicators. 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. (2019).[24] 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 2017, 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. (2019). 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. (2019) 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. (2019).

To illustrate this in more detail, in Koop et al. (2019), which used the old Statistical Office Region classification in place prior to 1995, what is now the North East and North West of England NUTS1

[23] These data are 'balanced' in the sense of balancing the income and production approaches to measuring GVA.
[24] Available at `https://www.escoe.ac.uk/download/2601/`

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 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. (2019), 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 2018, cover the period 1998-2017 or 1997-2017 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 minimize 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 emphasize (as is detailed in the data appendix for Koop et al. (2019)) 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. (2019) 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[25]) with the secondary aim of minimizing 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 A.1 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%

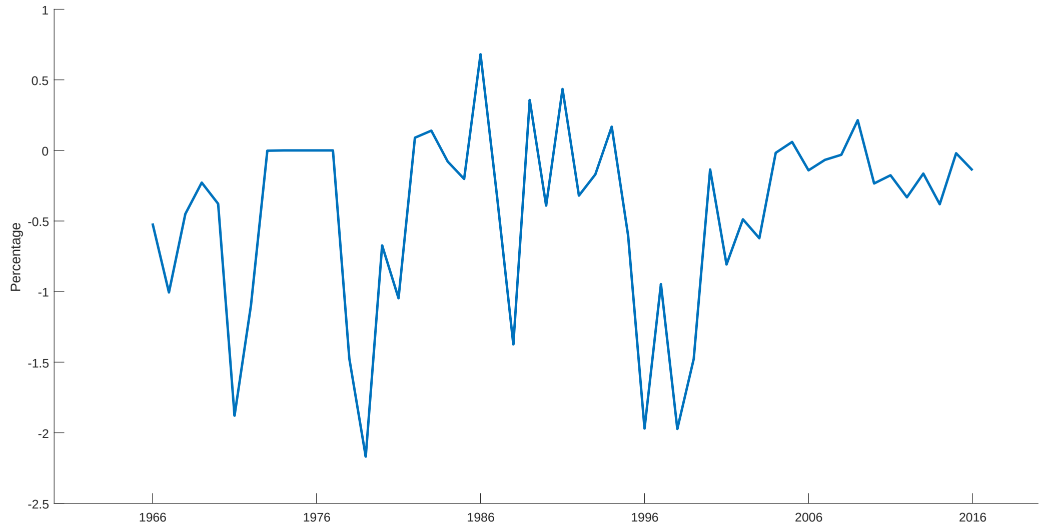
The final or latest vintage regional nominal GVA data are taken to be a combination (with the geographical reconcilition outlined above) of: (i) the historical 1966–1996 regional nominal GVA (income approach) data as released by the ONS[26] but without taking this back to first release, as described in Koop et al (2019), so that data revisions are accommodated[27]; and (ii) the December

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

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

[27]The ONS's historical database picks up estimates from successive yearly publications of Regional Trends. But the

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



2018 release of regional nominal GVA(B) data covering the period 1998–2017. The 1997 regional data are not available in balanced form, but the December 2018 data release from the ONS does provide estimates via the income approach and we use these. For the UK as a whole, the February 2019 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 2019 data vintage. Regional real GVA(B) data from 1998-2017 for each NUTS 1 (indeed NUTS 2 also) region of the UK are available from the ONS's December 2017 publication.[28]. 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 summarize, our annual final vintage regional real GVA dataset combines the GVA(B) data produced for the first time in December 2018 (covering 1998–2017) with the final

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.

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

vintage, nominal regional data for the earlier period (1966–1997), deflated using a UK-wide measure of inflation.

A.3 Additional quarterly economic indicators

In addition to GVA data for the UK as a whole and for the NUTS 1 regions, we include four further quarterly macroeconomic 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 (\$: £). 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[29], and the UK consumer price index data from the ONS[30]. The oil price data were taken from Thomson Reuters Datastream[31] as the quarterly average price. The US dollar : UK pound exchange rate series was downloaded from the Bank of England's Millennium Database[32].

In our model we also make use of two additional data series relating to economic conditions in each region. The first of these is the claimant count rate measure of unemployment, accessed through `http://www.nomisweb.co.uk`. This provided claimant count rate data for NUTS1 regions of the UK back to the early 1970s. Prior to this, we assume that each region's claimant count rate evolved in line with the claimant count rate of the UK as a whole. While available monthly, we consider these data when aggregated to the quarterly frequency. The second regional indicator is the Business Optimism Indicator produced by the Confederation of British Industry (CBI). This is available on a regional basis from 1980 onward through Thomson Reuters Datastream. These data are produced for 11 regions of the UK (these reflect the NUTS 1 regional definitions with the exception of London and the South East of England where responses are combined together into a single region). Prior to 1980, we use the UK series for all regions.

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 the main paper. 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), in the main paper, as a multivariate linear regression model:

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

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

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

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

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

where $\mathbf{X}_t = \mathrm{I}_n \otimes [1, \mathbf{y}'_{t-1}, \dots, \mathbf{y}'_{t-p}]$ is an $n \times k$ matrix and $\beta = vec([\Phi_0, \Phi_1, \dots, \Phi_p]')$ is a $k \times 1$ vector of coefficients. We can stack (B.1) over time $t = 1, \dots T$, 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 $\Sigma = \mathrm{diag}(\Sigma_1, \dots, \Sigma_T)$.

The multivariate stochastic volatility specification used in this paper is given in (6), (7) and (8). The Dirichlet-Laplace priors are given in (9), (10), (11), (12). We use the same Dirichlet-Laplace priors for the $\mathbf{a}$'s and assume $i = 1, \dots, m$

$$a_i \sim N(0, \psi_i^a \vartheta_{i,a}^2 \tau_a^2), \tag{B.4}$$

$$\psi_i^a \sim \mathrm{Exp}(\frac{1}{2}), \tag{B.5}$$

$$\vartheta_{i,a} \sim \mathrm{Dir}(\alpha_a, \dots, \alpha_a), \tag{B.6}$$

$$\tau_a \sim \mathrm{G}(m\alpha_a, \frac{1}{2}). \tag{B.7}$$

Finally, we assume

$$\omega_{h_j}^2 \sim \mathrm{IG}(\nu_{h_j}, S_{h_j}), \quad \text{for } i = 1, \dots, n. \tag{B.8}$$

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:

$$\beta | \bullet \sim N(\hat{\beta}, \mathbf{K}_\beta^{-1}), \tag{B.9}$$

where

$$\mathbf{K}_\beta = \mathbf{X}'\Sigma^{-1}\mathbf{X} + \mathbf{S}_\beta^{-1}, \quad \hat{\beta} = \mathbf{K}_\beta^{-1}(\mathbf{X}'\Sigma^{-1}\mathbf{y}), \tag{B.10}$$

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

The conditional posterior for $\mathbf{a}$ takes the following form:

$$\mathbf{a} | \bullet \sim N(\hat{\mathbf{a}}, \mathbf{K}_a^{-1}), \tag{B.11}$$

where

$$\mathbf{K}_a = \mathbf{E}'\mathbf{D}^{-1}\mathbf{E} + \mathbf{S}_a^{-1}, \quad \hat{\mathbf{a}} = \mathbf{K}_a^{-1}(\mathbf{E}'\mathbf{D}^{-1}\epsilon), \tag{B.12}$$

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

$$\mathbf{E}_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ -\epsilon_{1,t} & 0 & 0 & 0 & 0 & 0 \\ 0 & -\epsilon_{1,t} & -\epsilon_{2,t} & 0 & 0 & 0 \\ 0 & 0 & 0 & -\epsilon_{1,t} & -\epsilon_{2,t} & -\epsilon_{3,t} \end{bmatrix}, \tag{B.13}$$

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

To deal with stochastic volatility, we follow Chan and Eisenstat (2018) 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 (2018) and use

$$\mathbf{h}_0|\bullet \sim N(\hat{\mathbf{h}}_0, \mathbf{K}_{\mathbf{h}_0}^{-1}), \tag{B.14}$$

where

$$\mathbf{K}_{\mathbf{h}_0} = \quad \mathbf{V}_h^{-1} + \Sigma_h^{-1} \quad , \quad \hat{\mathbf{h}}_0 = \mathbf{K}_{\mathbf{h}_0}^{-1}(\mathbf{V}_h^{-1}\mathbf{a}_h + \Sigma_h^{-1}\mathbf{h}_1). \tag{B.15}$$

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

$$\omega_{h_j}^2|\bullet \sim IG(\nu_{h_j} + \tfrac{T}{2}, S_{h_j} + \tfrac{1}{2}\textstyle\sum_{t=1}^{T}(h_{j,t} - h_{j,t-1})^2), \quad \text{for } j = 1, \ldots, n. \tag{B.16}$$

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

$$(\psi_j^\beta)^{-1}|\bullet \sim iG(\tfrac{\vartheta_{j,\beta}\tau_\beta}{|\beta_j|}, 1), \quad \text{for } j = 1, \ldots, k \tag{B.17}$$

$$\tau_\beta|\bullet \sim GIG(k(\alpha_\beta - 1), 1, 2\sum_{j=1}^{K}\frac{|\beta_j|}{\vartheta_{j,\beta}}), \tag{B.18}$$

$$R_{j,\beta}|\bullet \sim GIG(\alpha_\beta - 1, 1, 2|\beta_j|), \quad \text{for } j = 1, \ldots, k \tag{B.19}$$

and

$$\vartheta_{j,\beta} = \frac{R_{j,\beta}}{\sum_{j=1}^{k} R_{j,\beta}}. \tag{B.20}$$

We use notation where GIG is the generalized 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:

$$(\psi_i^a)^{-1}|\bullet \sim iG(\tfrac{\vartheta_{i,a}\tau_a}{|a_i|}, 1), \quad \text{for } i = 1, \ldots, m \tag{B.21}$$

$$\tau_a|\bullet \sim GIG(m(\alpha_a - 1), 1, 2\sum_{i=1}^{m}\frac{|a_j|}{\vartheta_{i,a}}), \tag{B.22}$$

$$R_{i,a}|\bullet \sim GIG(\alpha_a - 1, 1, 2|a_i|), \quad \text{for } i = 1, \ldots, m \tag{B.23}$$

and

$$\vartheta_{i,a} = \frac{R_{i,a}}{\sum_{i=1}^{m} R_{i,a}}. \tag{B.24}$$

B.1.3 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 (2018). The choices for the Dirichlet-Laplace hyperparameters, α_β, α_a, are the relatively noninformative default choices suggested by Bhattacharya et al. (2015). For a robustness check, we also consider the results when $\alpha_\beta = \alpha_a = 0.1$ and we find these results produce very similar results to our benchmark case of

$\alpha_\beta = \alpha_a = \frac{1}{2}$. To demonstrate, Figures B.1 through B.4 compare results using the different prior hyperparameter choices.

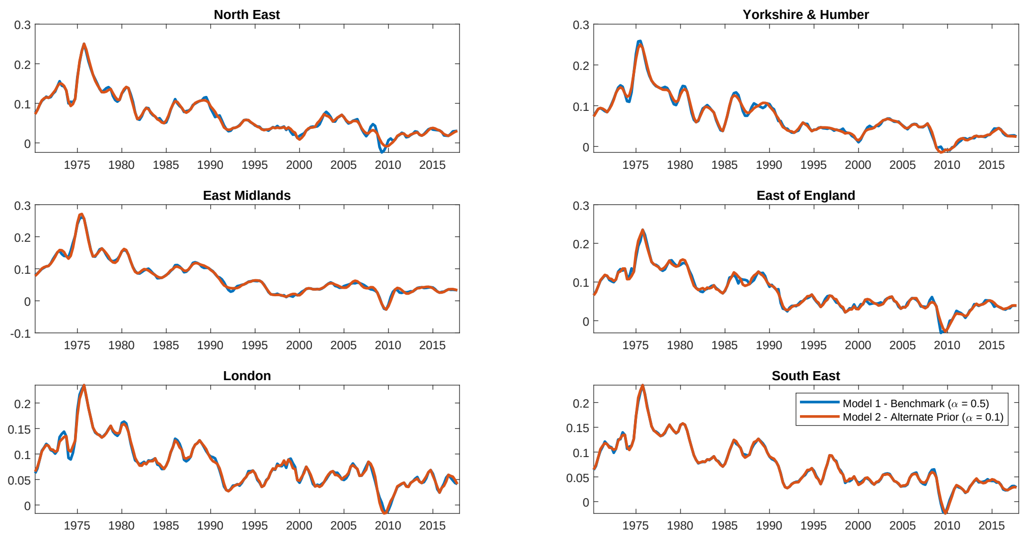


Figure B.1: Regional Nominal GVA

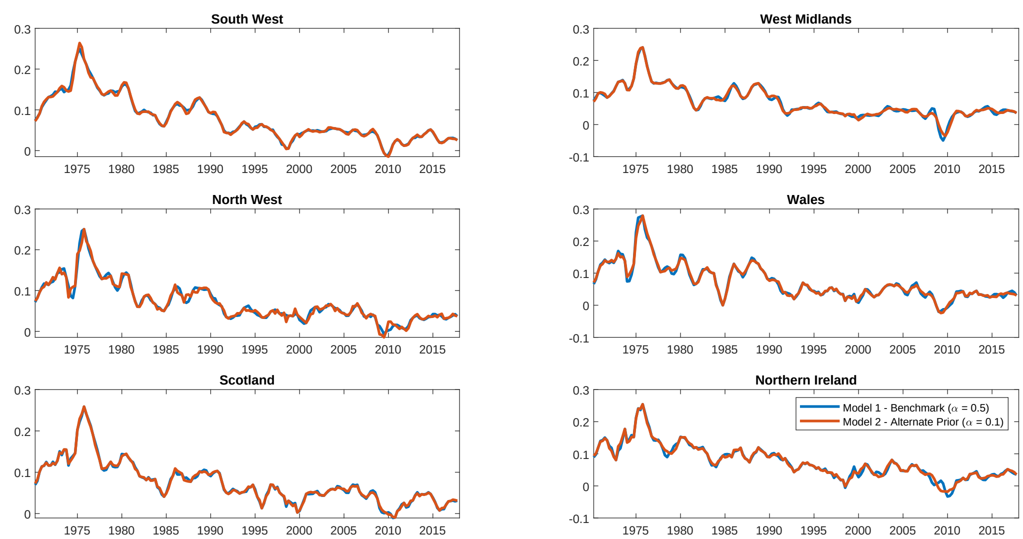


Figure B.2: Regional Nominal GVA

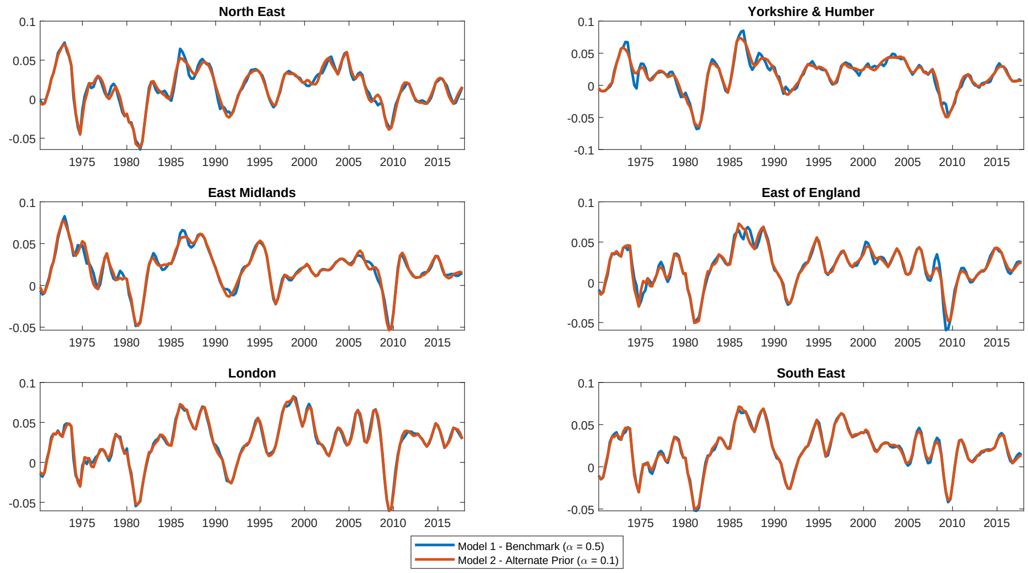


Figure B.3: Regional Real GVA

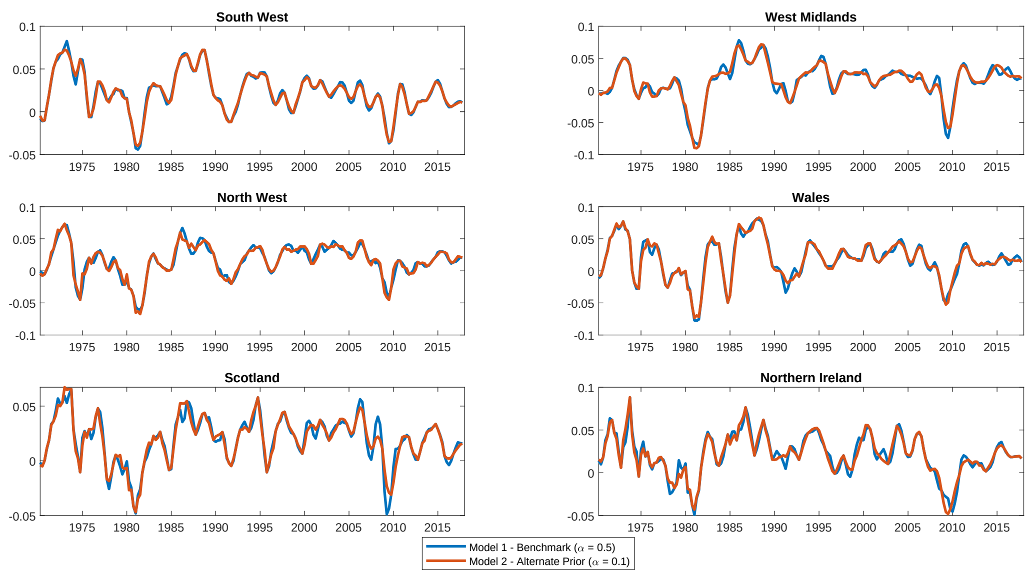


Figure B.4: Regional Real GVA

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:

$$\begin{bmatrix} y_t^{UK} \\ y_t^1 \\ y_t^2 \end{bmatrix} = \begin{bmatrix} \Phi_{qc} \\ \Phi_{ac} \end{bmatrix} + \begin{bmatrix} \Phi_{qq,1} & \Phi_{qa,1} \\ \Phi_{aq,1} & \Phi_{aa,1} \end{bmatrix} \begin{bmatrix} y_{t-1}^{UK} \\ y_{t-1}^1 \\ y_{t-1}^2 \end{bmatrix} + \ldots + \begin{bmatrix} \Phi_{qq,7} & \Phi_{qa,7} \\ \Phi_{aq,7} & \Phi_{aa,7} \end{bmatrix} \begin{bmatrix} y_{t-7}^{UK} \\ y_{t-7}^1 \\ y_{t-7}^2 \end{bmatrix} + \epsilon_t. \quad \text{(B.25)}$$

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

$$\Phi_{qq} = \left[\begin{array}{cccc} \Phi_{qq,1}, & \Phi_{qq,2}, & \Phi_{qq,3} & ,\ldots,\Phi_{qq,7} \end{array} \right], \quad \text{(B.26)}$$

$$\Phi_{qa} = \left[\begin{array}{cccc} \Phi_{qa,1}, & \Phi_{qa,2}, & \Phi_{qa,3} & ,\ldots,\Phi_{qa,7} \end{array} \right], \quad \text{(B.27)}$$

$$\Phi_{aq} = \left[\begin{array}{cccc} \Phi_{aq,1} & ,\Phi_{aq,2} & ,\Phi_{aq,3} & ,\ldots,\Phi_{aq,7} \end{array} \right], \quad \text{(B.28)}$$

$$\Phi_{aa} = \left[\begin{array}{cccc} \Phi_{aa,1} & ,\Phi_{aa,2}, & \Phi_{aa,3} & ,\ldots,\Phi_{aa,7} \end{array} \right]. \quad \text{(B.29)}$$

Then our state equation is

$$\mathbf{s}_t = \Gamma_s \mathbf{s}_{t-1} + \Gamma_z \mathbf{y}_{t-p:t-1}^{UK} + \Gamma_c + \Gamma_u u_{a,t}, \quad \text{(B.30)}$$

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:

$$\Gamma_s = \begin{bmatrix} \Phi_{qq} & 0 \\ \mathbf{I} & 0 \end{bmatrix}_{z\times z}, \Gamma_z = \begin{bmatrix} \Phi_{aq} \\ 0 \end{bmatrix}_{z\times p}, \Gamma_c = \begin{bmatrix} \Phi_{ac} \\ 0 \end{bmatrix}_{z\times 1}, \Gamma_u = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}_{z\times 2}, \quad \text{(B.31)}$$

we can obtain the measurement equation:

$$y_t^{UK} = \Lambda_{qs}\mathbf{s}_t + \Phi_{qq}\mathbf{y}_{t-p:t-1}^{UK} + \Phi_{ac} + u_{q,t}, \quad \text{(B.32)}$$

where

$$\Lambda_{qs} = \left[\begin{array}{cc} 0 & \Phi_{qa} \end{array} \right]_{1\times z}. \quad \text{(B.33)}$$

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

$$\begin{bmatrix} y_t^{1,A} \\ y_t^{2,A} \end{bmatrix} = \Lambda_{as}\mathbf{s}_t + \Lambda_z \mathbf{y}_{t-p:t-1}^{UK} + \Phi_{qc}, \quad \text{(B.34)}$$

where

$$\Lambda_{as} = \begin{bmatrix} 0 & \Phi_{qa} \\ & M \end{bmatrix}, \Lambda_z = [\begin{array}{c} \Phi_{qq} \\ 0 \end{array}], \quad \text{(B.35)}$$

$$M = \begin{bmatrix} \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & 0 & 0 \\ 0 & \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & 0 \end{bmatrix}. \quad \text{(B.36)}$$

This incorporates the intertemporal restriction given in (2).

Finally, the cross-sectional restriction, (5), gives us an additional measurement equation. We have

$$y_t^{UK} = \mathbf{R}\mathbf{s}_t + \eta, \eta \sim N(0, \sigma_{cs}^2), \quad \text{(B.37)}$$

where

$$\mathbf{R} = \left[\begin{array}{ccc} \frac{1}{R} & \frac{1}{R} & 0 \end{array} \right]_{1\times z}. \quad \text{(B.38)}$$

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.30) and measurement equations given by (B.32), (B.34) and (B.37). 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.

B.2.1 The Cross-sectional Restriction Using Log-differenced Data

The proof that our cross-sectional restriction is correct and that UK GVA growth is an average of regional GVA growth rates for the R regions begins by noting you can write UK GVA growth in two ways:

$$y_t^{UK} = \ln(Y_t^{UK}) - \ln(Y_{t-1}^{UK}) \tag{B.39}$$

$$y_t^{UK} = \ln(\sum_{r=1}^{R} Y_t^r) - \ln(\sum_{r=1}^{R} Y_{t-1}^r). \tag{B.40}$$

If we take a (first order) Taylor series expansion of the log of the average in the second equation and use the fact that the geometric mean is never larger than the arithmetic mean (and the difference between the two will be small if the quarterly movements are small relative to the quarterly average) we obtain $\ln(\sum_{r=1}^{R} Y_t^r) \simeq \frac{1}{R}\sum_{r=1}^{R} \ln Y_t^r + R\ln R$. Hence,

$$y_t^{UK} \simeq \frac{1}{R}\sum_{r=1}^{R} \ln Y_t^r - \frac{1}{R}\sum_{r=1}^{R} \ln Y_{t-1}^r$$

$$y_t^{UK} \simeq \frac{1}{R}\sum_{r=1}^{R} \left(\ln Y_t^r - \ln Y_{t-1}^r\right)$$

$$y_t^{UK} \simeq \frac{1}{R}\sum_{r=1}^{R} y_t^r$$

C Empirical Appendix

C.1 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.1 and C.2 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 2017Q4. 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.3 and C.4. Note that, just as with the nominal GVA data, the oil price has the largest impact.

We also provide a connectedness table for $h = 4$ which can be seen to lie between the results for $h = 1$ and $h = 20$ (see Table C.5).

Table C.1: Connectedness Estimates for 2017Q4, 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	72.4%	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%	0.0%	**0.1%**
CPI	0.0%	73.9%	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%**
Bank Rate	0.0%	0.0%	73.7%	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%**
Ex. rate	0.0%	0.0%	0.0%	73.1%	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%**
Oil price	0.0%	0.0%	0.0%	0.0%	73.3%	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%**
North E.	0.0%	0.0%	0.0%	0.0%	0.0%	73.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.1%**
York. and H.	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	74.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.1%**
E. Midlands	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	68.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
E. of England	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	69.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
London	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	73.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
South E.	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	72.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
South West	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	73.6%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
West Midlands	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	73.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
North West	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%	73.2%	0.0%	0.0%	0.0%	**0.2%**
Wales	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%	70.7%	0.0%	0.0%	**0.2%**
Scotland	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%	71.3%	0.0%	**0.2%**
N. Ireland	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%	0.0%	70.5%	**0.2%**
To	**0.1%**	**0.1%**	**0.1%**	**0.1%**	**0.1%**	**0.1%**	**0.1%**	**0.2%**	**0.2%**	**0.2%**	**0.2%**	**0.2%**	**0.2%**	**0.2%**	**0.3%**	**0.3%**	**0.3%**	**0.2%**

Table C.2: Connectedness Estimates for 2017Q4, 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	91.9%	3.5%	3.6%	1.2%	1.8%	1.4%	1.3%	2.6%	2.0%	1.5%	2.7%	2.5%	1.6%	1.5%	1.5%	1.1%	2.5%	**32.4%**
CPI	3.2%	92.4%	2.0%	1.5%	1.3%	0.9%	1.2%	3.5%	2.5%	1.6%	1.3%	1.1%	1.5%	1.4%	3.3%	1.9%	2.1%	**30.3%**
Bank Rate	3.2%	2.0%	92.4%	1.2%	1.1%	1.5%	1.5%	2.2%	3.6%	2.0%	1.9%	1.5%	1.3%	1.7%	1.8%	2.0%	1.9%	**30.4%**
Ex. rate	0.8%	1.0%	0.8%	91.9%	5.3%	2.2%	2.0%	1.5%	1.3%	1.8%	1.9%	2.0%	1.9%	1.7%	3.7%	2.1%	1.9%	**31.8%**
Oil price	1.0%	0.7%	0.7%	4.5%	92.0%	1.6%	1.3%	1.7%	2.3%	2.1%	1.9%	1.6%	1.8%	3.9%	2.4%	1.9%	1.9%	**31.2%**
North E.	0.8%	0.5%	0.9%	1.9%	1.6%	92.2%	1.2%	2.0%	2.0%	1.8%	1.9%	1.9%	1.7%	2.2%	4.2%	2.6%	2.4%	**29.8%**
York. and H.	0.7%	0.7%	0.9%	1.7%	1.4%	1.3%	92.5%	1.8%	1.8%	2.4%	2.3%	2.6%	2.3%	1.9%	2.1%	2.1%	2.5%	**28.6%**
E. Midlands	1.3%	1.9%	1.2%	1.2%	1.6%	1.9%	1.6%	90.1%	5.1%	3.4%	2.5%	2.5%	1.9%	3.2%	2.5%	2.5%	3.1%	**37.3%**
E. of England	0.9%	1.3%	1.9%	1.0%	1.9%	1.7%	1.5%	4.8%	90.3%	2.2%	2.4%	2.1%	2.5%	2.4%	4.2%	2.7%	2.7%	**36.2%**
London	0.7%	0.8%	1.0%	1.4%	1.8%	1.5%	2.0%	3.2%	2.2%	92.0%	2.1%	1.5%	2.5%	2.3%	2.4%	2.4%	2.2%	**29.9%**
South E.	1.2%	0.6%	1.0%	1.4%	1.6%	1.6%	1.9%	2.4%	2.4%	2.2%	91.6%	2.1%	2.0%	2.0%	2.1%	1.7%	5.6%	**32.0%**
South West	1.2%	0.6%	0.8%	1.5%	1.4%	1.7%	2.3%	2.5%	2.2%	1.6%	2.2%	92.0%	3.4%	2.5%	2.0%	1.7%	2.3%	**30.1%**
West Midlands	0.7%	0.7%	0.7%	1.4%	1.5%	1.4%	2.0%	1.8%	2.6%	2.6%	2.0%	3.3%	91.8%	2.6%	2.8%	2.4%	2.3%	**31.0%**
North West	0.6%	0.6%	0.7%	1.1%	2.7%	1.6%	1.4%	2.6%	2.2%	2.0%	1.8%	2.2%	2.3%	92.4%	3.3%	2.4%	2.3%	**29.8%**
Wales	0.5%	1.3%	0.7%	2.2%	1.6%	2.8%	1.4%	1.9%	3.4%	2.0%	1.6%	1.5%	2.4%	3.1%	91.0%	2.2%	5.3%	**33.7%**
Scotland	0.5%	0.8%	0.9%	1.3%	1.4%	2.0%	1.5%	2.1%	2.4%	2.2%	1.5%	1.5%	2.2%	2.3%	2.6%	92.0%	7.6%	**32.7%**
N. Ireland	0.9%	0.8%	0.8%	1.1%	1.2%	1.6%	1.6%	2.3%	2.1%	1.8%	4.3%	1.8%	1.8%	2.1%	5.3%	6.6%	90.7%	**36.0%**
To	**18.1%**	**17.9%**	**18.6%**	**25.6%**	**29.1%**	**26.7%**	**25.8%**	**38.9%**	**40.1%**	**33.1%**	**34.2%**	**31.7%**	**33.2%**	**36.8%**	**46.0%**	**38.3%**	**48.8%**	**32.0%**

Table C.3: Real GVA Growth Connectedness Estimates for 2017Q4, 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	81.7%	1.7%	2.0%	0.7%	1.1%	0.8%	0.7%	1.5%	1.0%	0.9%	1.9%	1.5%	0.9%	0.9%	0.8%	0.6%	1.4%	**18.3%**
CPI	1.6%	83.0%	1.1%	0.8%	0.7%	0.5%	0.7%	1.9%	1.4%	1.0%	0.8%	0.6%	0.8%	0.8%	1.9%	1.1%	1.3%	**17.0%**
Bank Rate	1.7%	1.1%	82.2%	0.7%	0.7%	0.9%	0.9%	1.5%	2.2%	1.1%	1.0%	0.8%	0.7%	1.0%	1.1%	1.2%	1.1%	**17.8%**
Ex. rate	0.5%	0.6%	0.6%	81.8%	3.1%	1.1%	1.0%	0.9%	0.7%	1.0%	1.1%	1.1%	1.0%	0.9%	2.1%	1.1%	1.1%	**18.2%**
Oil price	0.7%	0.5%	0.5%	2.6%	82.5%	0.9%	0.7%	1.0%	1.1%	1.2%	1.0%	0.9%	1.0%	1.9%	1.3%	1.1%	1.1%	**17.5%**
North E.	0.5%	0.3%	0.6%	1.0%	0.9%	83.4%	0.7%	1.0%	1.2%	1.0%	1.2%	1.0%	0.9%	1.2%	2.3%	1.3%	1.3%	**16.6%**
York. and H.	0.4%	0.4%	0.6%	1.0%	0.8%	0.8%	83.7%	1.0%	1.1%	1.3%	1.3%	1.3%	1.3%	1.1%	1.2%	1.2%	1.4%	**16.3%**
E. Midlands	0.8%	1.0%	0.9%	0.8%	1.0%	1.0%	1.0%	79.1%	2.6%	1.9%	1.3%	1.4%	1.0%	1.7%	1.4%	1.4%	1.8%	**20.9%**
E. of England	0.5%	0.8%	1.2%	0.6%	1.0%	1.1%	0.9%	2.5%	79.7%	1.2%	1.2%	1.2%	1.3%	1.4%	2.4%	1.5%	1.4%	**20.3%**
London	0.4%	0.6%	0.6%	0.8%	1.0%	0.9%	1.1%	1.8%	1.3%	82.8%	1.1%	1.0%	1.3%	1.3%	1.4%	1.3%	1.3%	**17.2%**
South E.	0.9%	0.4%	0.6%	0.9%	0.9%	1.1%	1.1%	1.3%	1.3%	1.2%	81.9%	1.1%	1.0%	1.2%	1.1%	1.0%	2.9%	**18.1%**
South West	0.8%	0.4%	0.5%	0.9%	0.8%	0.9%	1.2%	1.4%	1.4%	1.1%	1.2%	82.9%	1.7%	1.3%	1.2%	0.9%	1.4%	**17.1%**
West Midlands	0.4%	0.4%	0.4%	0.8%	0.9%	0.8%	1.2%	1.0%	1.4%	1.4%	1.1%	1.6%	83.1%	1.5%	1.5%	1.3%	1.3%	**16.9%**
North West	0.4%	0.4%	0.5%	0.7%	1.4%	1.0%	0.9%	1.4%	1.3%	1.2%	1.1%	1.2%	1.4%	82.6%	2.0%	1.3%	1.3%	**17.4%**
Wales	0.3%	0.8%	0.5%	1.3%	0.9%	1.6%	0.8%	1.1%	1.9%	1.1%	1.0%	1.0%	1.3%	1.8%	80.3%	1.2%	3.1%	**19.7%**
Scotland	0.3%	0.5%	0.6%	0.8%	0.9%	1.1%	0.9%	1.2%	1.4%	1.2%	0.9%	0.8%	1.2%	1.4%	1.4%	81.8%	3.6%	**18.2%**
N. Ireland	0.5%	0.5%	0.5%	0.7%	0.7%	1.0%	0.9%	1.4%	1.2%	1.0%	2.3%	1.1%	1.0%	1.2%	2.9%	2.9%	80.2%	**19.8%**
To	**10.7%**	**10.4%**	**11.7%**	**15.0%**	**16.8%**	**15.6%**	**14.8%**	**22.0%**	**22.5%**	**18.9%**	**19.4%**	**17.7%**	**17.9%**	**20.6%**	**25.8%**	**20.6%**	**26.8%**	18.1%

Table C.4: Real GVA Growth Connectedness Estimates for 2017Q4, 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	10.2%	3.4%	3.1%	2.2%	2.2%	6.1%	5.8%	6.0%	8.3%	5.3%	6.4%	5.7%	6.6%	10.6%	6.1%	6.3%	5.7%	**89.8%**
CPI	8.4%	7.6%	4.1%	2.8%	2.6%	5.9%	5.6%	5.8%	7.9%	5.1%	5.9%	5.4%	5.8%	10.2%	5.7%	5.8%	5.3%	**92.4%**
Bank Rate	8.9%	4.8%	6.1%	2.8%	2.6%	6.0%	5.6%	5.8%	8.1%	5.1%	6.0%	5.3%	5.9%	10.2%	5.7%	5.8%	5.3%	**93.9%**
Ex. rate	8.3%	3.4%	3.1%	2.5%	2.2%	6.1%	6.0%	6.2%	8.4%	5.3%	6.3%	5.6%	7.6%	10.7%	6.2%	6.3%	5.7%	**97.5%**
Oil price	8.0%	3.1%	2.9%	2.0%	2.2%	6.3%	6.2%	6.1%	8.7%	5.4%	6.5%	5.8%	6.6%	11.5%	6.3%	6.5%	5.8%	**97.8%**
North E.	8.2%	3.0%	2.8%	2.0%	2.1%	7.0%	6.1%	6.2%	8.6%	5.4%	6.5%	5.9%	6.8%	10.7%	6.3%	6.4%	5.8%	**93.0%**
York. and H.	8.3%	2.9%	2.7%	1.9%	2.0%	6.3%	6.7%	6.3%	8.6%	5.4%	6.5%	5.9%	6.9%	10.8%	6.4%	6.5%	5.8%	**93.3%**
E. Midlands	8.3%	3.1%	2.8%	2.0%	2.1%	6.2%	6.0%	7.2%	8.5%	5.4%	6.4%	5.8%	6.8%	10.8%	6.3%	6.4%	5.8%	**92.8%**
E. of England	8.2%	2.9%	2.8%	1.9%	2.1%	6.2%	6.0%	6.3%	9.7%	5.5%	6.5%	5.9%	6.8%	10.8%	6.3%	6.5%	5.8%	**90.3%**
London	8.3%	3.0%	2.8%	2.0%	2.1%	6.2%	6.0%	6.2%	8.5%	6.2%	6.5%	5.9%	6.8%	10.8%	6.3%	6.4%	5.8%	**93.8%**
South E.	8.3%	3.0%	2.8%	1.9%	2.1%	6.1%	6.0%	6.2%	8.6%	5.5%	7.4%	5.9%	6.8%	10.8%	6.3%	6.4%	5.9%	**92.6%**
South West	8.2%	3.0%	2.8%	1.9%	2.1%	6.2%	6.1%	6.2%	8.6%	5.4%	6.5%	6.8%	6.8%	10.8%	6.4%	6.4%	5.8%	**93.2%**
West Midlands	8.2%	3.1%	2.9%	2.0%	2.1%	6.2%	6.1%	6.2%	8.5%	5.3%	6.4%	5.8%	8.0%	10.7%	6.2%	6.4%	5.8%	**92.0%**
North West	8.1%	2.8%	2.6%	1.8%	2.0%	6.3%	6.0%	6.3%	8.6%	5.4%	6.6%	5.9%	6.9%	11.9%	6.4%	6.5%	5.9%	**88.1%**
Wales	8.3%	3.1%	2.8%	2.0%	2.1%	6.3%	6.1%	6.3%	8.5%	5.4%	6.4%	5.8%	6.8%	10.8%	7.1%	6.4%	5.8%	**92.9%**
Scotland	8.2%	2.9%	2.7%	1.8%	2.0%	6.2%	6.1%	6.3%	8.6%	5.5%	6.5%	5.9%	6.9%	10.7%	6.4%	7.5%	5.9%	**92.5%**
N. Ireland	8.2%	2.8%	2.7%	1.9%	2.0%	6.3%	6.1%	6.3%	8.6%	5.5%	6.5%	5.9%	7.0%	10.7%	6.4%	6.5%	6.7%	**93.3%**
To	**132.5%**	**50.3%**	**46.3%**	**33.0%**	**34.4%**	**99.0%**	**95.9%**	**98.8%**	**135.6%**	**85.9%**	**102.5%**	**92.7%**	**107.6%**	**171.5%**	**99.7%**	**101.4%**	**92.1%**	**92.9%**

Table C.5: Real GVA Growth Connectedness Estimates for 2017Q4, 4 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	42.2%	2.5%	2.4%	1.2%	1.3%	3.4%	3.3%	4.6%	4.9%	4.0%	4.5%	4.6%	3.7%	4.7%	4.4%	3.8%	4.3%	**57.8%**
CPI	3.9%	60.6%	3.1%	1.1%	1.0%	1.9%	1.9%	3.4%	2.9%	2.2%	2.2%	2.3%	2.4%	2.5%	3.3%	2.5%	2.7%	**39.4%**
Bank Rate	6.5%	2.8%	56.2%	1.1%	1.0%	2.3%	2.1%	3.0%	3.9%	2.5%	2.8%	2.5%	2.6%	2.7%	2.8%	2.6%	2.6%	**43.8%**
Ex. rate	5.8%	2.1%	1.8%	27.5%	2.1%	3.8%	4.6%	5.8%	5.7%	4.8%	5.5%	4.2%	4.3%	6.0%	6.9%	4.3%	4.7%	**72.5%**
Oil price	2.9%	1.1%	1.3%	1.4%	6.0%	5.8%	14.3%	3.8%	8.4%	3.6%	4.9%	3.3%	2.9%	27.2%	4.4%	4.8%	4.0%	**94.0%**
North E.	4.3%	1.6%	1.8%	1.5%	1.5%	27.2%	5.9%	5.5%	6.7%	4.3%	5.2%	5.1%	4.7%	8.0%	6.7%	5.0%	4.9%	**72.8%**
York. and H.	4.3%	1.6%	1.6%	1.4%	1.4%	6.1%	23.6%	6.5%	7.3%	4.9%	5.7%	5.3%	4.7%	9.1%	6.2%	5.2%	5.1%	**76.4%**
E. Midlands	4.6%	2.1%	1.9%	1.4%	1.5%	4.7%	4.6%	30.8%	6.8%	4.4%	4.8%	5.2%	4.8%	7.3%	5.3%	4.8%	5.1%	**69.2%**
E. of England	4.7%	1.8%	2.1%	1.2%	1.4%	4.5%	4.8%	5.5%	30.7%	5.0%	6.1%	5.0%	4.2%	7.4%	5.5%	5.4%	4.7%	**69.3%**
London	4.9%	1.7%	1.7%	1.4%	1.5%	4.6%	5.0%	5.3%	6.9%	27.4%	5.7%	5.4%	4.7%	7.7%	5.8%	5.3%	4.9%	**72.6%**
South E.	4.9%	1.6%	1.7%	1.4%	1.5%	4.4%	4.7%	5.3%	7.1%	5.3%	29.6%	5.3%	4.4%	7.4%	5.1%	4.9%	5.2%	**70.4%**
South West	4.7%	1.6%	1.7%	1.4%	1.4%	4.4%	4.7%	7.1%	6.9%	4.1%	5.1%	30.1%	4.6%	7.4%	5.3%	4.6%	4.9%	**69.9%**
West Midlands	4.4%	1.7%	1.7%	1.5%	1.4%	4.1%	4.9%	5.5%	5.7%	4.1%	4.9%	4.7%	34.5%	6.8%	5.4%	4.5%	4.4%	**65.5%**
North West	4.1%	1.5%	1.6%	1.2%	1.6%	7.2%	5.4%	5.1%	7.3%	4.5%	5.2%	4.8%	4.7%	29.1%	6.0%	5.7%	4.9%	**70.9%**
Wales	4.6%	1.9%	1.8%	1.6%	1.5%	4.8%	5.4%	5.9%	6.4%	4.4%	5.1%	5.5%	4.2%	7.5%	28.8%	4.7%	5.9%	**71.2%**
Scotland	4.3%	1.6%	1.6%	1.3%	1.4%	4.7%	4.9%	5.4%	6.6%	4.7%	5.5%	5.3%	4.2%	7.6%	5.7%	29.1%	5.9%	**70.9%**
N. Ireland	4.3%	1.6%	1.5%	1.3%	1.4%	4.9%	5.1%	5.9%	6.6%	4.7%	5.6%	5.7%	4.8%	7.2%	6.0%	5.8%	27.6%	**72.4%**
To	**73.3%**	**28.9%**	**29.4%**	**21.4%**	**22.8%**	**71.9%**	**81.5%**	**83.7%**	**100.2%**	**67.8%**	**78.8%**	**74.2%**	**65.8%**	**126.6%**	**84.8%**	**73.9%**	**74.0%**	**68.2%**

C.2 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 annualized 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.

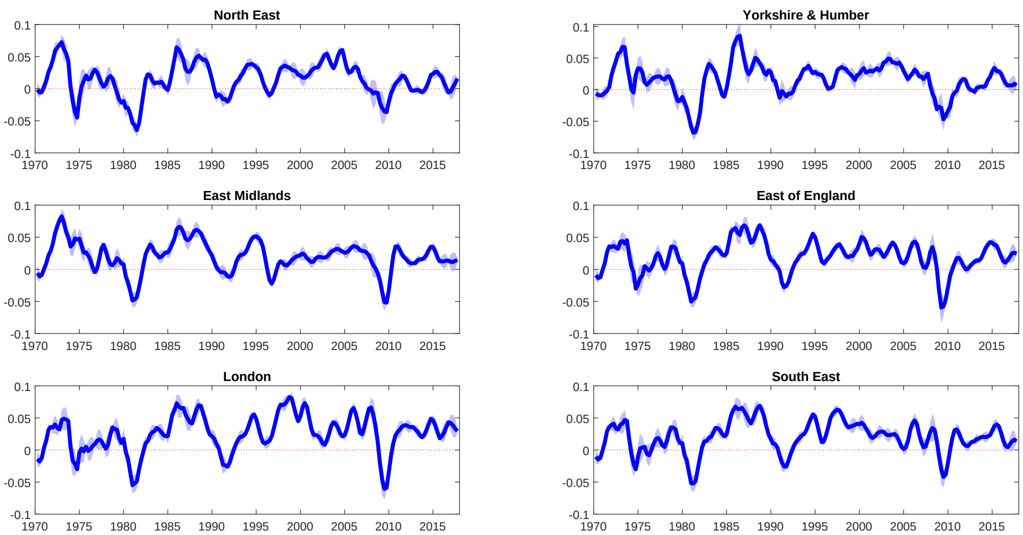


Figure C.1: Regional Real GVA Growth Rates: Estimates and Credible Intervals

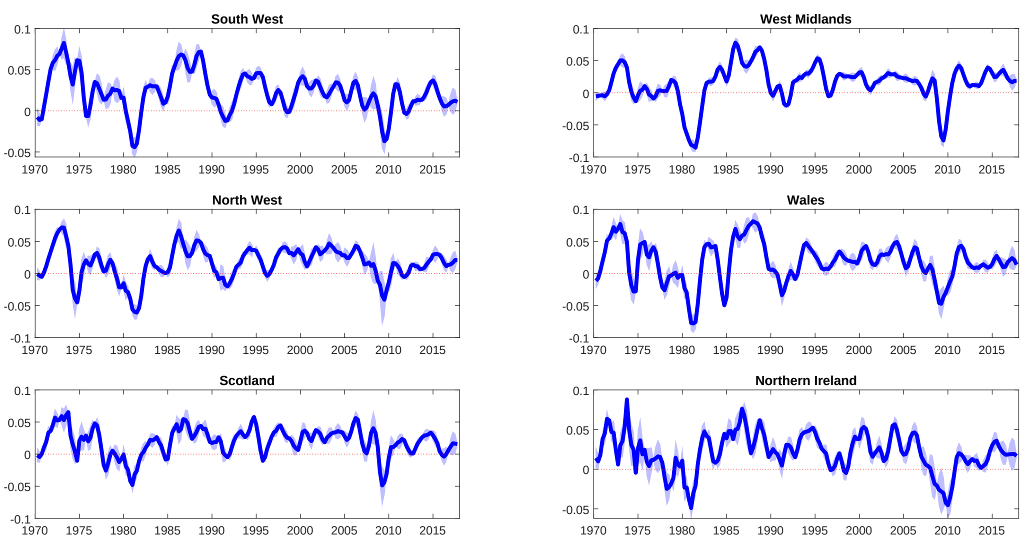


Figure C.2: Regional Real GVA Growth Rates: Estimates and Credible Intervals

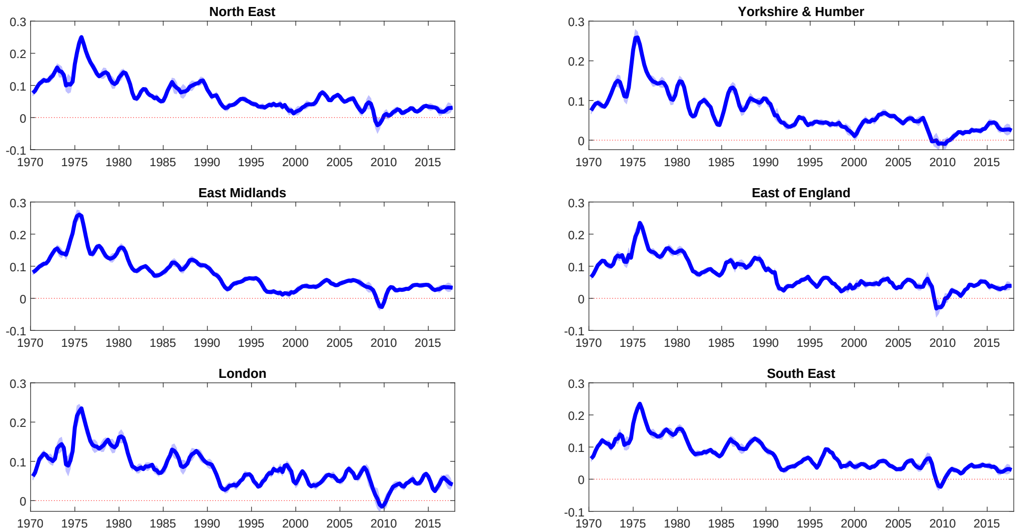


Figure C.3: Regional Nominal Growth Rates: Estimates and Credible Intervals

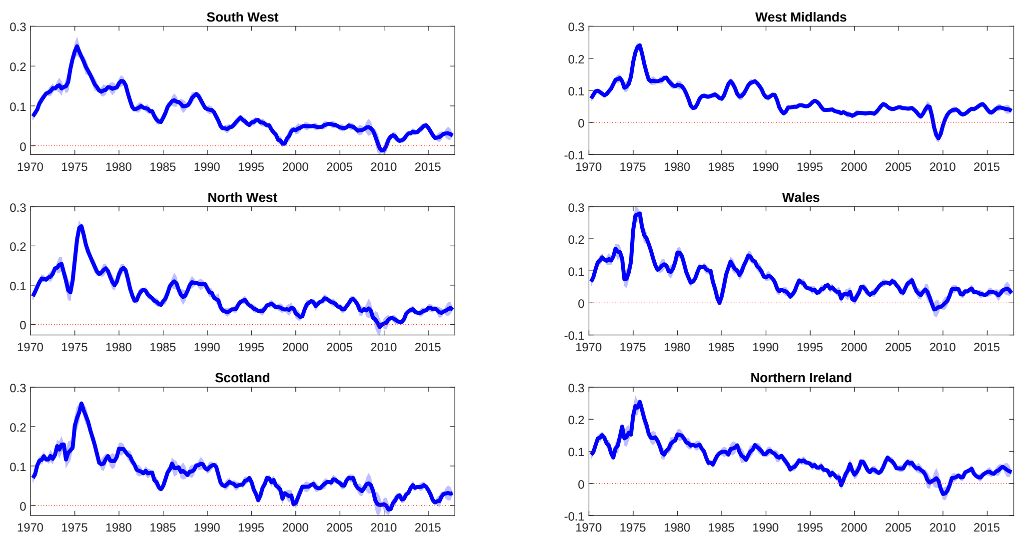


Figure C.4: Regional Nominal Growth Rates: Estimates and Credible Intervals

C.3 Results using Exact Growth Rates

Here we consider the modifications to our MF-VAR required when we model in exact growth rates rather than logarithmic differences as in the main paper. Then we explore the sensitivity of our empirical results to this choice.

We use the following notational conventions, emphasizing that here we model in exact quarter-on-quarter growth rates:

- $t = 1, .., T$ 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.
- $y_t^{UK} = \left(\frac{Y_t^{UK} - Y_{t-1}^{UK}}{Y_{t-1}^{UK}}\right)$ is the quarterly (quarter-on-quarter) growth rate 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 for quarter 4 of each year, but not in other quarters.
- $y_t^{r,A} = \left(\frac{Y_t^{r,A} - Y_{t-4}^{r,A}}{Y_{t-4}^{r,A}}\right)$ is annual GVA growth in region r. It is observed, but only for quarter 4 of each year. Let $y_t^A = \left(y_t^{1,A}, .., y_t^{R,A}\right)'$ denote the vector of annual GVA growth rates for the R regions.
- $y_t^r = \left(\frac{Y_t^r - Y_{t-1}^r}{Y_{t-1}^r}\right)$ is the quarterly (quarter-on-quarter) growth rate in GVA in region r. It is never observed. Let $y_t^Q = \left(y_t^1, .., y_t^R\right)'$ denote the vector of quarterly year-on-year GVA growth rates for the R regions.

The MF-VAR is again specified in $y_t = \left(y_t^{UK}, y_t^{Q\prime}\right)'$, plus the additional macroeconomic and regional variables observed at the quarterly frequency. But the temporal and cross-sectional constraints need to be re-specified.

The temporal constraint is given as:

$$
\begin{aligned}
y_t^{r,A} = {} & \left(\frac{Y_{t-1}^r}{\sum_{j=0}^{3} Y_{t-4-j}^r}\right) y_t^r + \left(\frac{Y_{t-2}^r}{\sum_{j=0}^{3} Y_{t-4-j}^r}\right) 2y_{t-1}^r + \left(\frac{Y_{t-3}^r}{\sum_{j=0}^{3} Y_{t-4-j}^r}\right) 3y_{t-2}^r + \left(\frac{Y_{t-4}^r}{\sum_{j=0}^{3} Y_{t-4-j}^r}\right) 4y_{t-3}^r \\
& + \left(\frac{Y_{t-5}^r}{\sum_{j=0}^{3} Y_{t-4-j}^r}\right) 3y_{t-4}^r + \left(\frac{Y_{t-6}^r}{\sum_{j=0}^{3} Y_{t-4-j}^r}\right) 2y_{t-5}^r + \left(\frac{Y_{t-7}^r}{\sum_{j=0}^{3} Y_{t-4-j}^r}\right) y_{t-6}^r
\end{aligned} \tag{C.1}
$$

where the weights, $\left(\frac{Y_{t-j}^r}{Y_{t-4}^{r,A}}\right)$, denote the share of regional output in quarter $t-j$ in annual regional output from the previous year. To avoid a nonlinear measurement equation, we proxy these weights by 1/4.

The cross-sectional restriction that UK GVA is the sum of GVA across the R regions is re-specified as:

$$y_t^{UK} = \sum_{r=1}^{R} w_t^{*r} y_t^r + \eta_t \tag{C.2}$$

where $w_t^{*r} = \left(\frac{Y_{t-1}^r}{\sum_{r=1}^{R} Y_{t-1}^r} \right)$ is the share of regional output in aggregate output in quarter t and $\eta_t \sim N(0, \sigma_{cs}^2)$. We proxy w_t^{*r} by the observed annual shares, noting that we should expect to see little within-year variation in these weights.

We re-estimate our MF-VAR-SV model, using exact growth rates with the re-specified temporal and cross-sectional restrictions, (C.1) and (C.2), on the final vintage data to produce historical quarterly estimates of both nominal and real regional growth. Figure C.5 presents the quarterly nominal and real estimates alongside the UK growth rate. To aid in comparability with the published annual regional data, our quarterly estimates are again annualized (i.e. we take our quarterly regional GVA estimates, y_t^r, and construct and plot an annual change, $y_t^{r,A}$, using (C.1)).

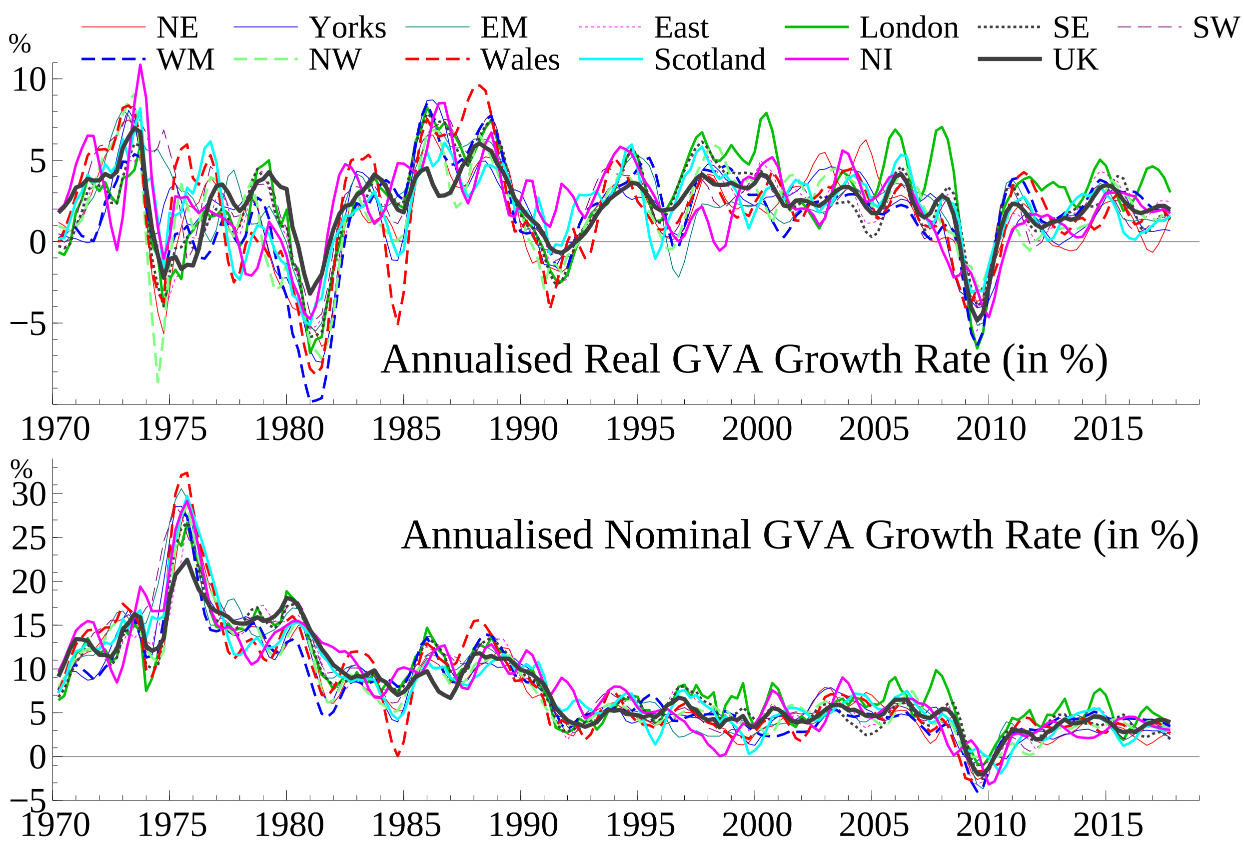


Figure C.5: Historical Estimates of Regional GVA Growth using Exact Growth Rates

Comparison of Figure C.5 with Figure 1 in the main paper, which uses logarithmic differences rather than exact growth rates, reassures that the choice of data transformation does not have a material effect on the movements of the quarterly regional estimates. The quarterly figures for the regions look very similar across Figures C.5 and 1, albeit as expected for large growth rates some differences between the scale of the two sets of estimates are seen. Table C.6 confirms how highly correlated the regional estimates in log differences are with those in exact growth rates.

Table C.6: Correlation Coefficient between log differences and exact growth rates

	Nominal GVA	Real GVA
North East	0.99	0.98
Yorkshire and The Humber	1.00	0.98
East Midlands	1.00	0.99
East of England	0.99	0.98
London	0.99	0.97
South East	0.99	0.99
South West	0.99	0.96
West Midlands	0.99	0.98
North West	0.99	0.97
Wales	0.99	0.98
Scotland	0.99	0.96
Northern Ireland	0.99	0.95

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