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

Gary Koop (Strathclyde, ESCoE), Stuart G. McIntyre (Strathclyde, ESCoE), James Mitchell (Warwick, ESCoE) & Aubrey Poon (Strathclyde, ESCoE)

NBP Workshop on Forecasting

26 November 2018

Background: Frequency and Timeliness

1. Regional UK nominal GVA data are currently available at annual frequency
2. Having regional data at higher frequency (e.g. quarterly) desirable
3. Regional UK GVA data are currently released with long delay (right now only have 2016)
4. Desirable to have quicker estimates
5. Other data are available more frequently and in a more timely fashion
6. GVA for UK as a whole are available quarterly and shorter release delay (right now have 2018Q1)
7. Can we use these higher frequency and more timely data to produce estimates (historical, present and future) of regional GVA growth?

Mixed Frequency Econometrics

1. Growing literature on building econometric models which combine data of different frequencies
2. Schorfheide and Song (2015). Real-time forecasting with a mixed-frequency VAR. Journal of Business Economic Statistics
3. Ghysels (2016). Macroeconomics and the reality of mixed frequency data. Journal of Econometrics
4. Brave, Butters and Justiniano (2016). Forecasting economic activity with mixed frequency Bayesian VARs. Federal Reserve Bank of Chicago Working Paper
5. McCracken, Owyang and Sekhposyan (2016). Real-time forecasting with a large, mixed frequency Bayesian VAR, Federal Reserve Bank of St. Louis Working Paper

Contribution

- Econometric contribution
  1. We build on Schorfheide and Song (2015) mixed frequency VAR state space model
  2. Addition of stochastic volatility (SV) (see Chan and Eisenstat (2018) JAE paper)
  3. Dirichlet-Laplace prior (see Bhattacharya et al (2015) JASA paper)
- Empirical Application
  1. Provide quarterly historical estimates of regional GVA for the 12 NUTS1 regions
  2. Derive a connectedness measure between the 12 NUTS1 regions
  3. Forecasting

Summary

UK Quarterly Nominal/Real GVA
12 NUTS1 Regional Annual Nominal/Real GVA

⇩

Mixed Frequency VAR with Stochastic Volality (MF-VAR-SV)

⇩

12 NUTS1 Regional 'Quarterly' Nominal/Real GVA

Model

- Let's define some notations:
  1. $t = 1, .., T$ runs at the *quarterly* frequency.
  2. $r = 1, .., R$ denotes the R regions in the UK.
  3. y_t^{UK} is the quarterly change in GVA in the UK. We observe this.
  4. $y_t^{r,A}$ is annual GVA growth in region r. It is observed, but only in quarter 4 of each year.
  5. y_t^r is the quarterly change in GVA in region r. It is never observed.
  6. y_t is a $[y_t^{UK}, y_t^{1,}, \ldots, y_t^R]$ $n \times 1$ vector containing quarterly growth rates. The regional ones are not observed.

Model(cont.)

- The MF-VAR-SV is a VAR using y_t as the dependent variables:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \ldots + \Phi_p y_{t-p} + u_t, u_t \sim N(0, \Sigma_t), \quad (1)$$

- To estimate the latent historical quarterly changes in GVA for each region y_t^r:
  - We impose two measurement equations that implies two restrictions:
- Inter-temporal restriction:

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

Model(cont.)

- Cross-sectional restriction of Doran (1992) ReStat:

$$y_t^{UK} = \frac{1}{R}\sum_{r=1}^{R} y_t^r + \eta, \eta \sim N(0, \sigma_{cs}^2), \tag{3}$$

- 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.

Model(cont.)

- VAR estimation
- We can rewrite equation (1) into a standard linear regression matrix form:

$$\mathbf{y}_t = \mathbf{X}_t \beta + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_t), \tag{4}$$

- where $\mathbf{X}_t = \mathrm{I}_n \otimes [1, \mathbf{y}'_{t-1}, \ldots, \mathbf{y}'_{t-p}]$ is $n \times k$ matrix and $\beta = vec([\mathbf{b}_0, \mathbf{B}_1, \ldots, \mathbf{B}_p]')$ is $k \times 1$ vector of coefficients.
- Σ_t is assume to follow a Cogley and Sargent (2005) structure:

$$\Sigma_t^{-1} = \mathbf{L}' \mathbf{D}_t^{-1} \mathbf{L}, \tag{5}$$

- $\mathbf{L}$ is $n \times n$ lower triangular matrix with ones on the diagonal.

Model(cont.)

- The off diagonal terms of the lower triangular matrix can be decomposed as $\mathbf{a} = (a_{1,1}, a_{2,1}, \ldots, a_{n,1}, a_{2,1}, \ldots, a_{n,n-1})'$ $m \times 1$ vector. $\mathbf{D}_t = \text{diag}(\exp(h_{1,t}), \ldots, \exp(h_{n,t}))$ and the log-volatilities $\mathbf{h}_t = (h_{1,t}, \ldots, h_{n,t})'$ evolves according to a random walk:

$$\mathbf{h}_t = \mathbf{h}_{t-1} + \nu_t, \nu_t \sim N(0, \Sigma_h), \tag{6}$$

- where $\Sigma_h = \text{diag}(\omega_{h_1}^2, \ldots, \omega_{h_n}^2)$. We follow Chan and Eisenstat (2018) and estimate the initial condition $\mathbf{h}_0$, $\mathbf{h}_0 \sim N(\mathbf{a}_h, \mathbf{V}_h)$.

Dirichlet-Laplace priors

- In our model, we have more low frequency variables than high frequency variables. This is opposite to Schorfheide and Song (2015).
- To impose parsimony in our model, we implement the Dirichlet-Laplace priors on both the β and $\mathbf{a}$.
- For example: let's assume that the $\beta = (\beta_1, \ldots, \beta_k)'$, then the Dirichlet-Laplace priors follows for $j = 1, \ldots, k$

$$\beta_j \sim N(0, \psi_j^{\beta} \vartheta_{j,\beta}^2 \tau_\beta^2), \tag{7}$$

$$\psi_j^{\beta} \sim \text{Exp}(\tfrac{1}{2}), \quad \vartheta_{j,\beta} \sim \text{Dir}(\alpha, \ldots, \alpha), \quad \tau_\beta \sim \text{G}(k\alpha, \tfrac{1}{2}). \tag{8}$$

- We follow Bhattacharya et al. (2015) and implement a non-informative shrinkage hyperparameter of $\alpha = 0.5$.

Dirichlet-Laplace priors

- Why Dirichlet-Laplace priors?
  - Comparison to the Lasso
    - $\beta_j \sim N(0, \psi_j^{\beta}), \psi_j^{\beta} \sim Exp(\frac{\lambda}{2}), \lambda \tilde{} G(a_0, b_0),$
  - Dirichlet-Laplace priors are global-local (GL) shrinkage priors
  - GL shrinkage priors produce posterior distributions with good empirical and theoretical properties.
  - DL priors can effectively shrink small coefficients and reliably estimate the coefficients of important variables simultaneously.
  - GL shrinkage priors have improved posterior concentrations, what does this mean? The posterior distributions of the β_j converges to the true posteriors.
  - Implementation is simple and requires less a-priori input from the researcher.

Data

1. Annual nominal and real GVA growth data from 1967 through 2016 (seasonally adjusted): **final vintage** and first release (for forecasting)
2. NUTS-1 regions
3. Data for NUTS-1 regions goes back to 1995; real GVA(B) data back to 1997
4. ONS nominal historical regional GVA data back to 1966; deflated (by UK deflator) for real database (but we allow for an error when imposing)
5. Statistical regions changed
6. Need to reconcile data prior to 1995
7. We also use extra UK quarterly variables in the MF-VAR
8. Inflation, interest rates, change in oil prices and exchange rates

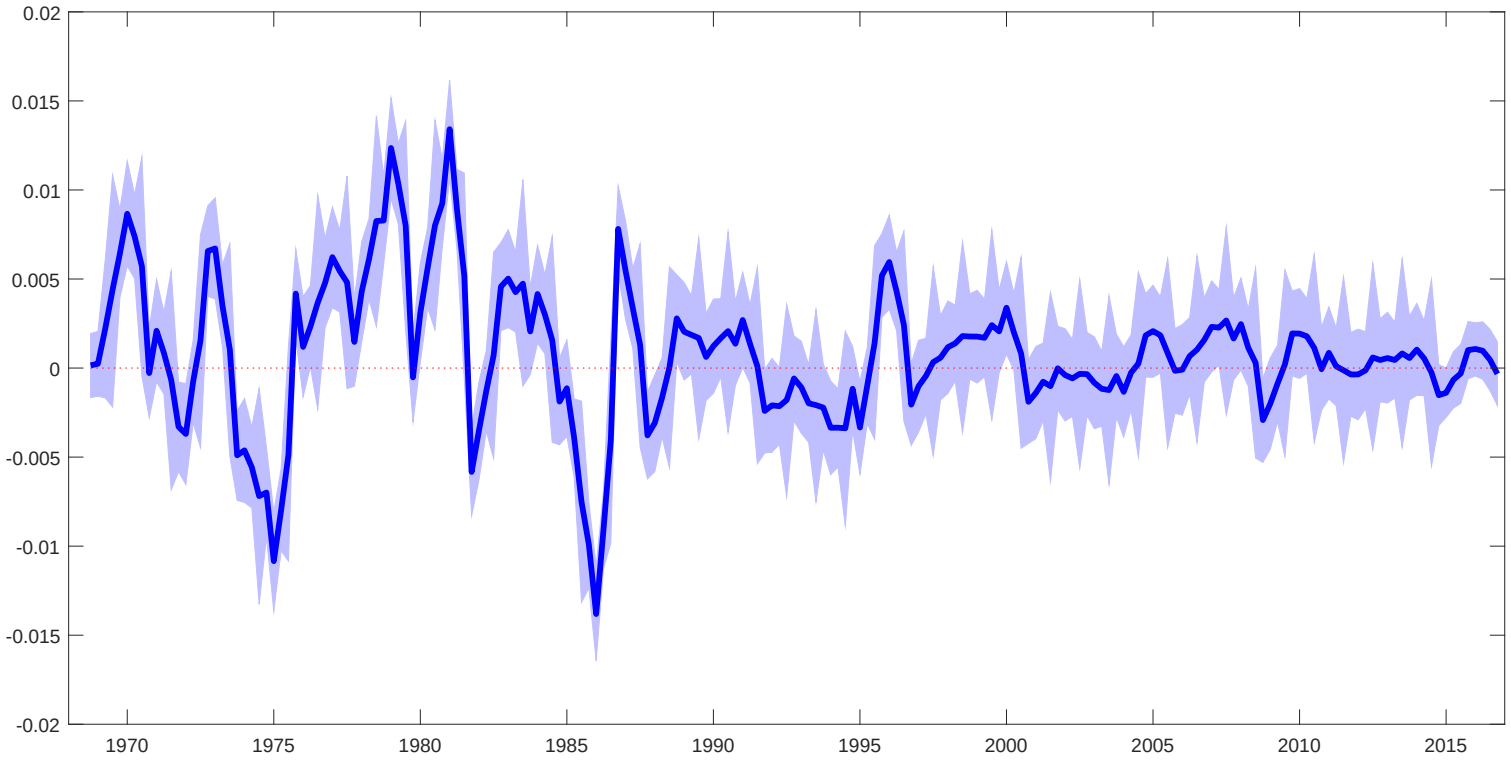
Estimation

- We estimate 17 variables MF-VAR-SV with $p = 7$ lags for both Nominal and Real GVA.
- Bayesian MCMC methods
  - Precision based methods of Chan and Jeliazkov (2009) and Chan and Eisenstat (2018).
  - Faster and more efficient. See Joshua Chan's Notes of Bayesian Macroeconometrics on his personal website.
- Marginal likelihood
  - We found overwhelming evidence for SV. This is consistent with the findings of Chan and Eisenstat (2018).
  -

Log-Marginal Likelihood	MF-VAR	MF-VAR-SV
Nominal GVA	3463.7	4355.3
Real GVA	3649.0	4589.8

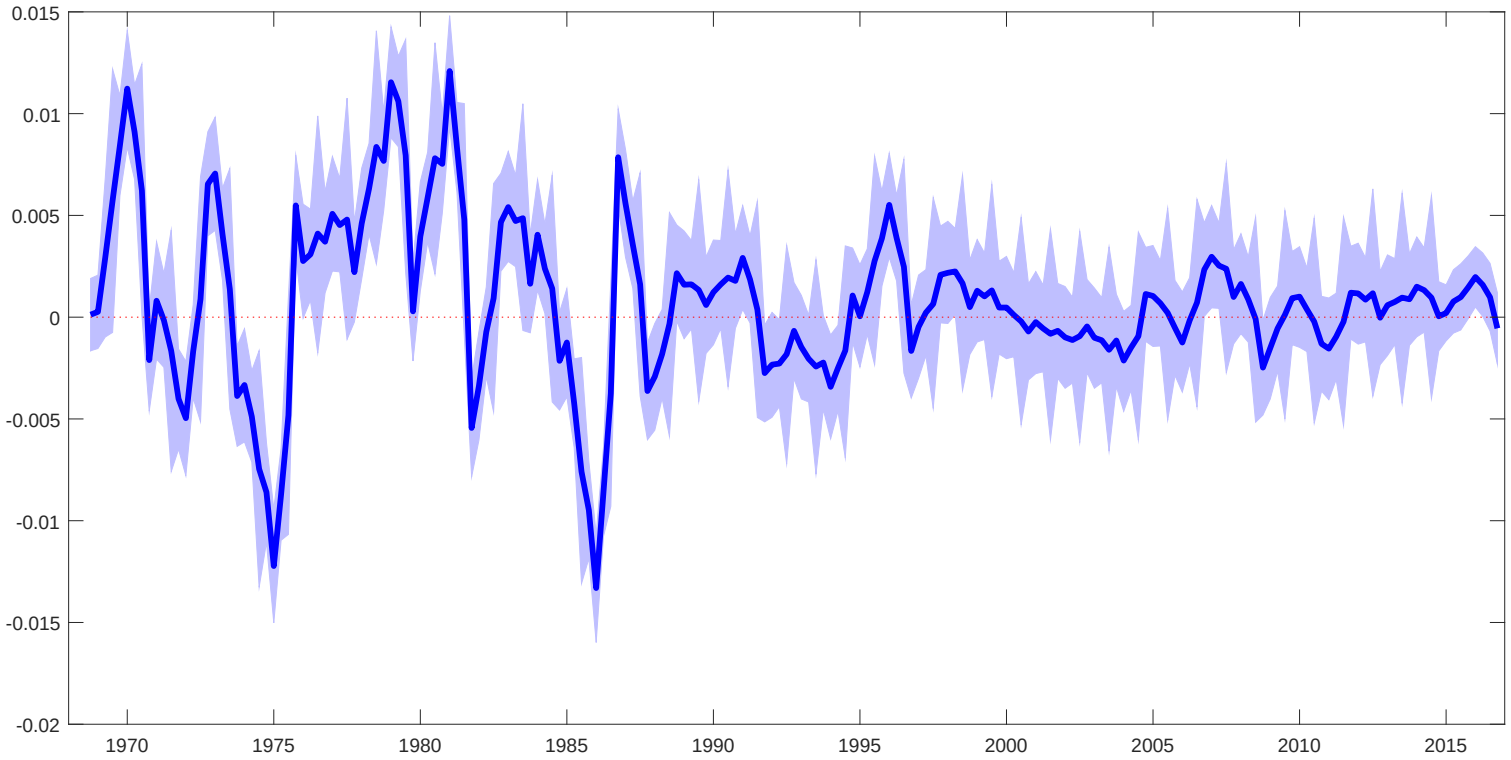
Cross-sectional errors

- Nominal GVA



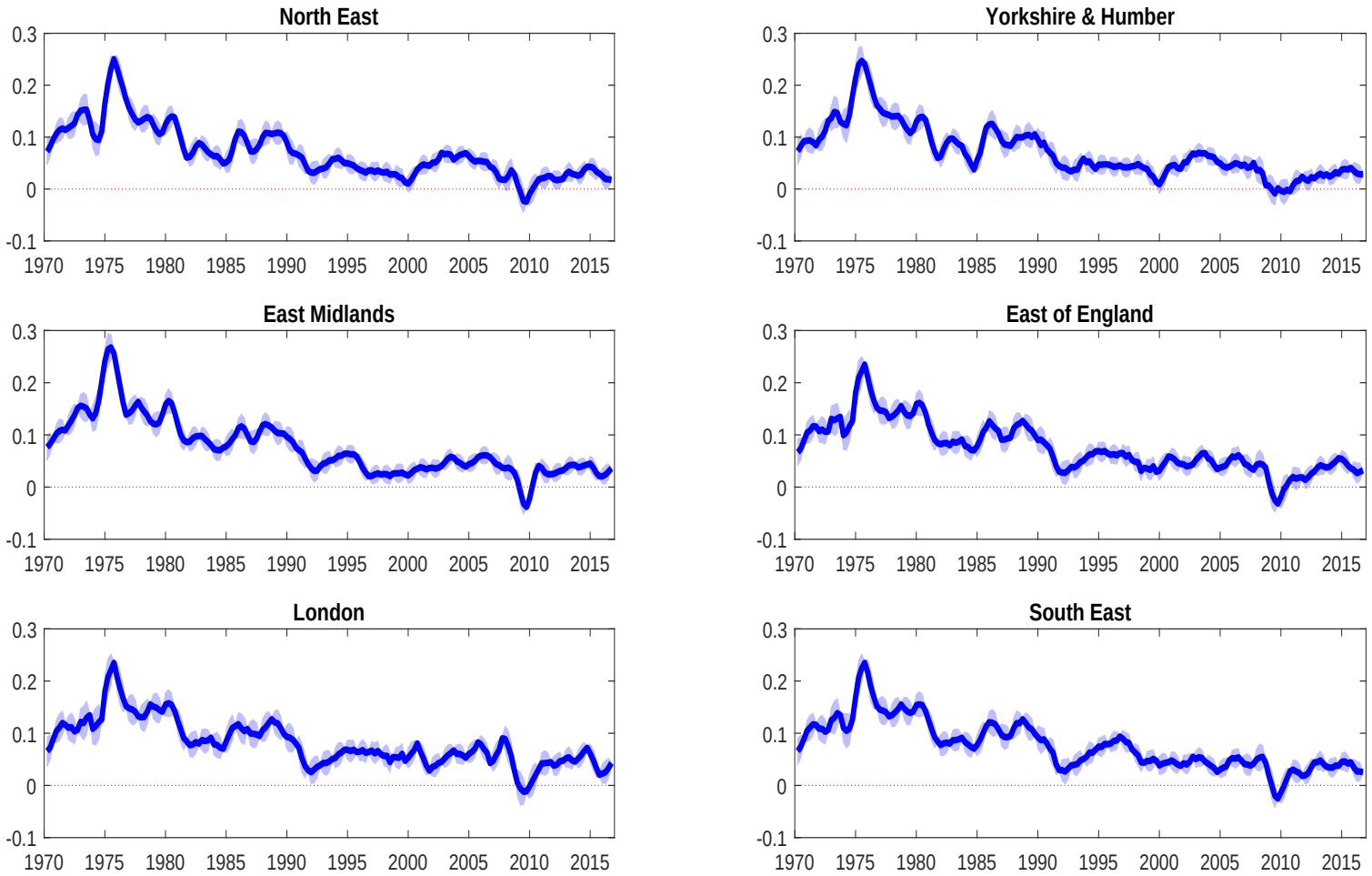
Cross-sectional errors

- Real GVA

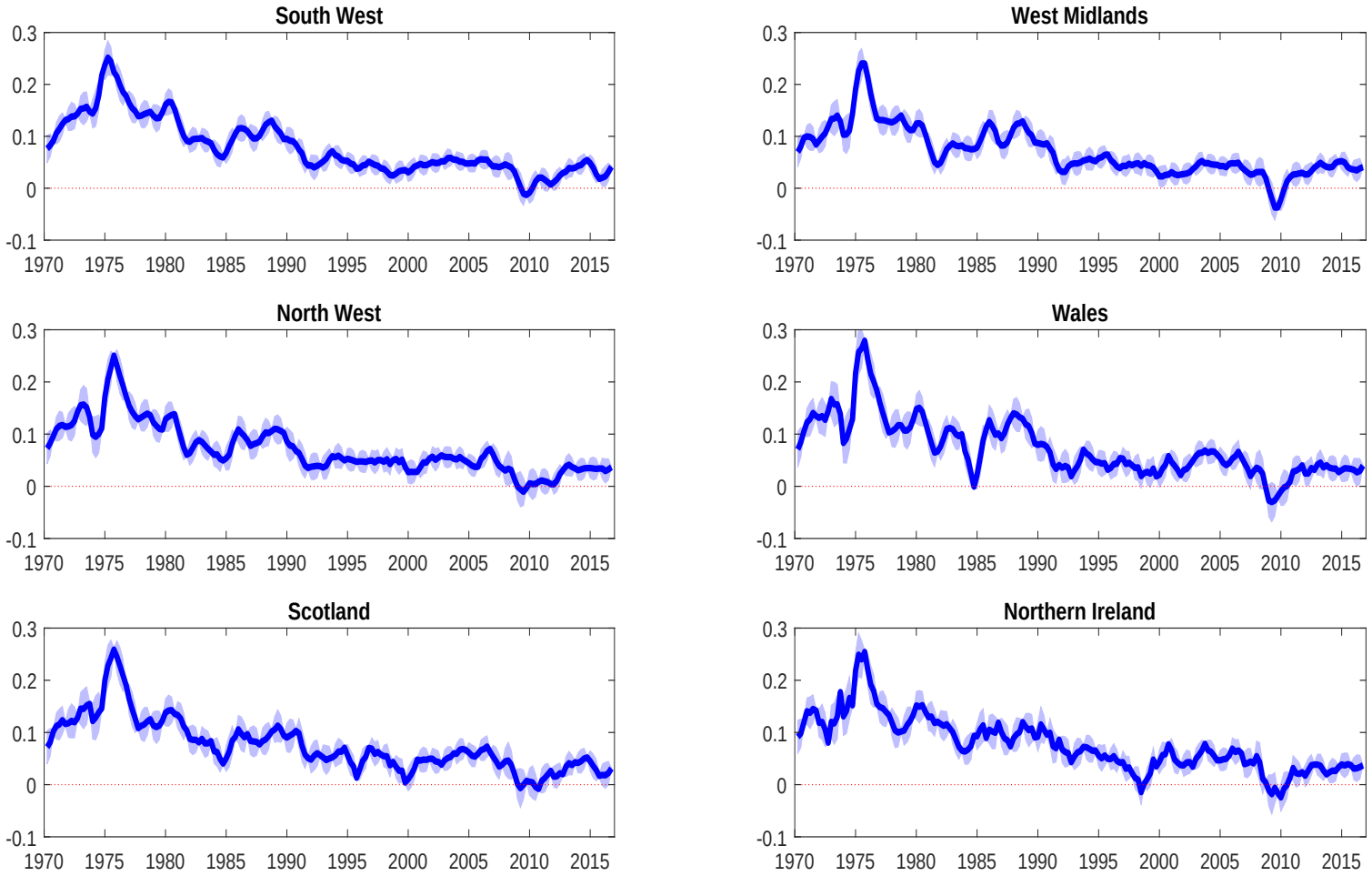


Empirical Results - Nominal GVA

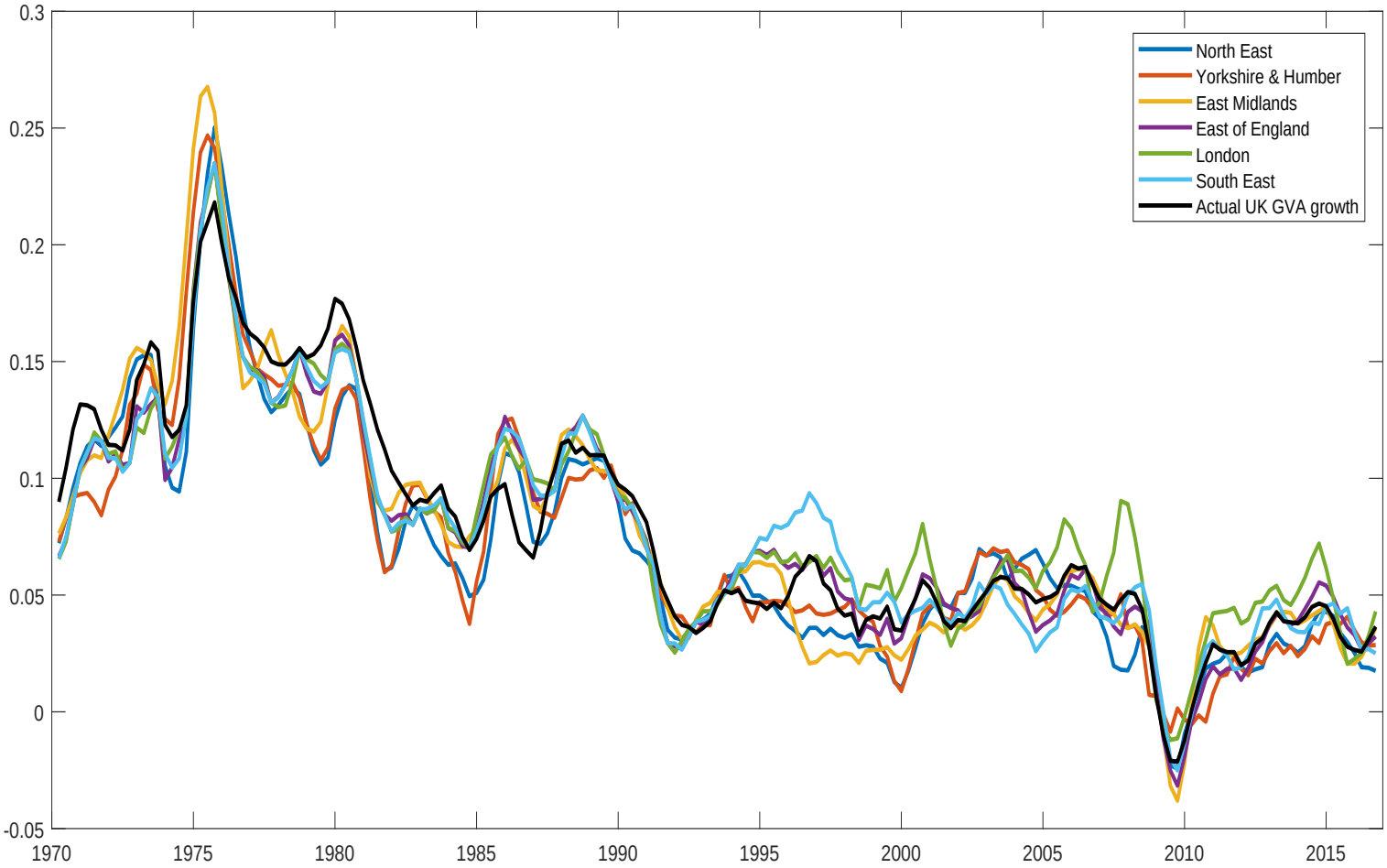
Annualised growth rates



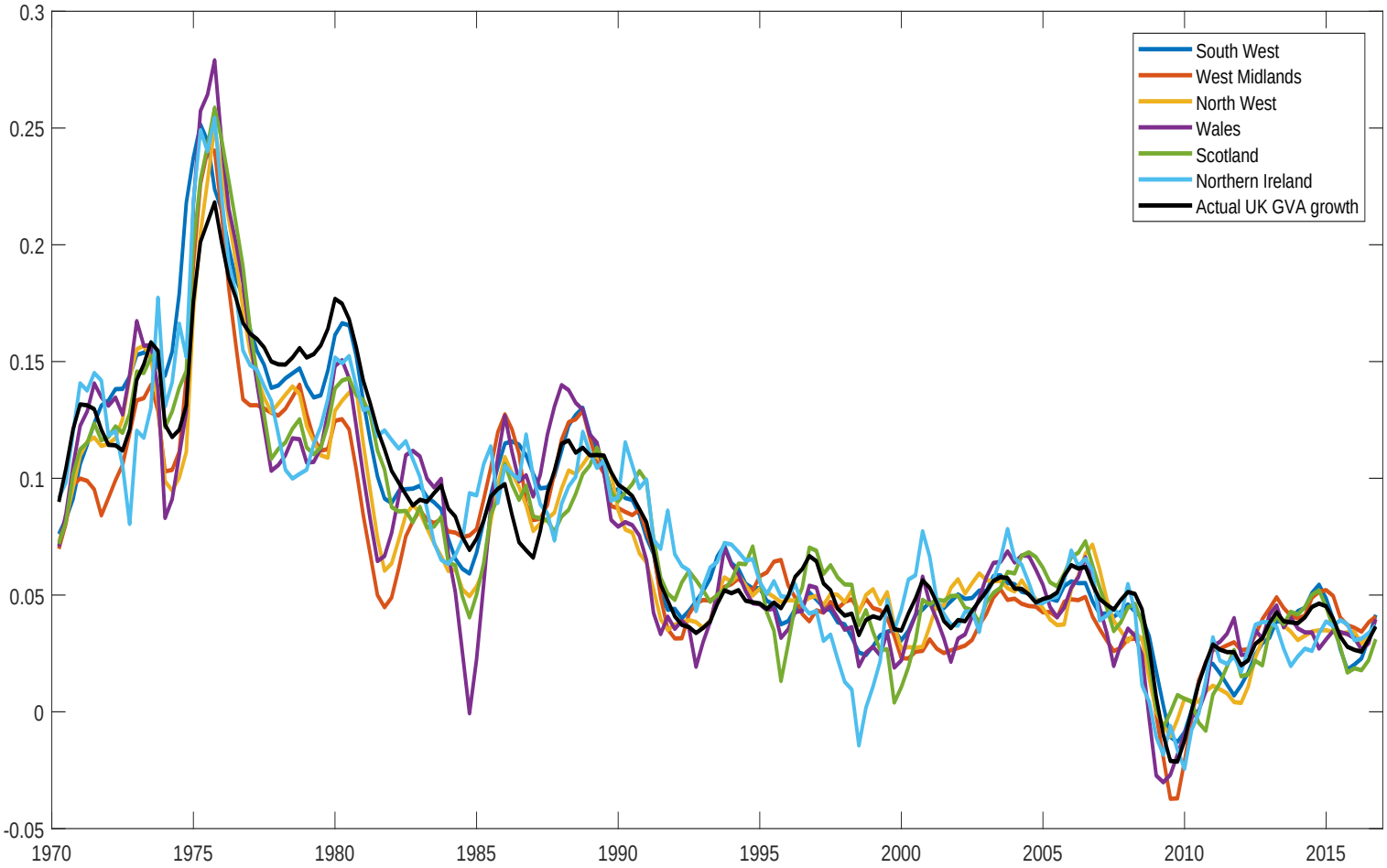
Empirical Results - Nominal GVA



Empirical Results - Nominal GVA

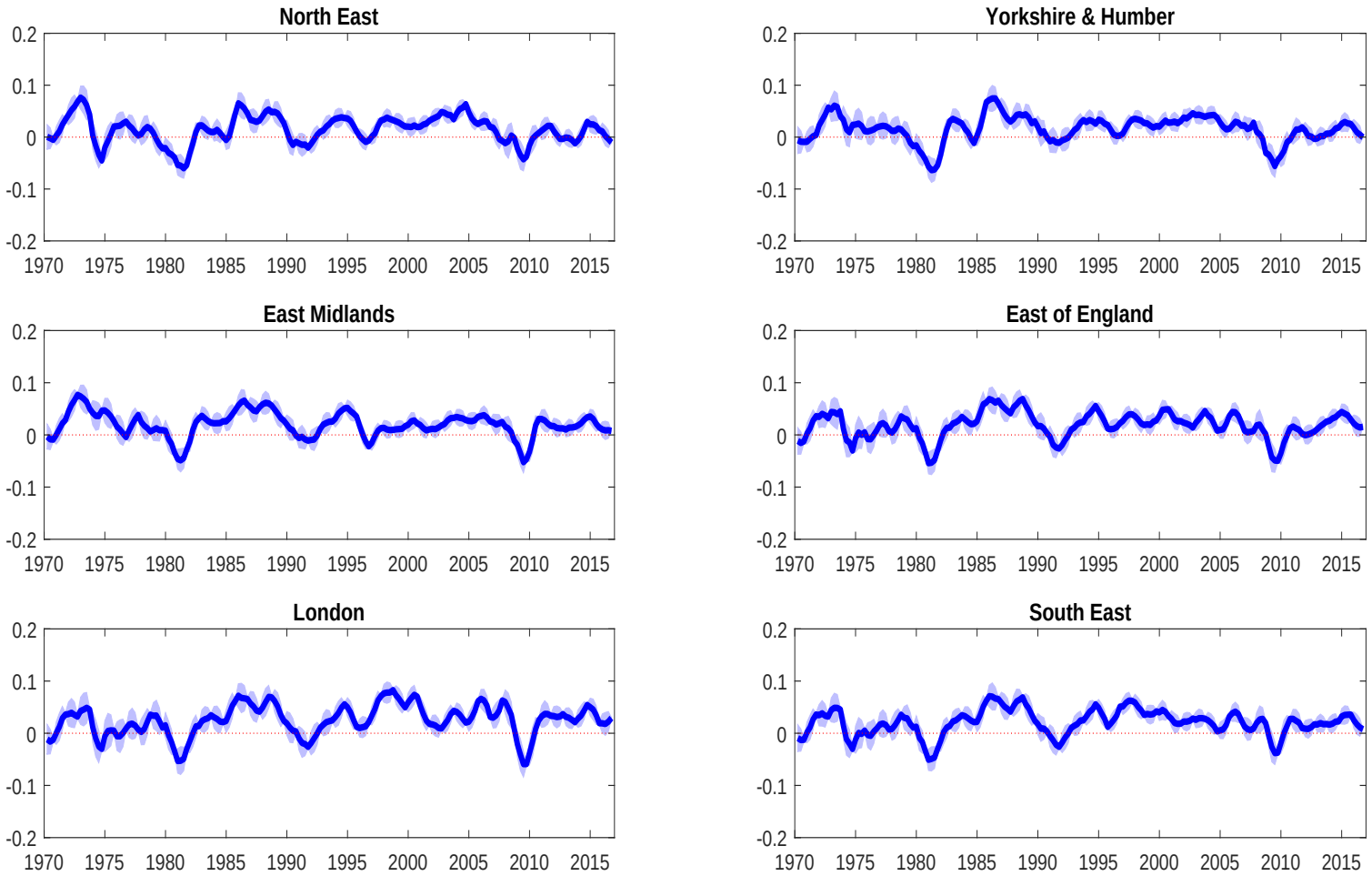


Empirical Results - Nominal GVA

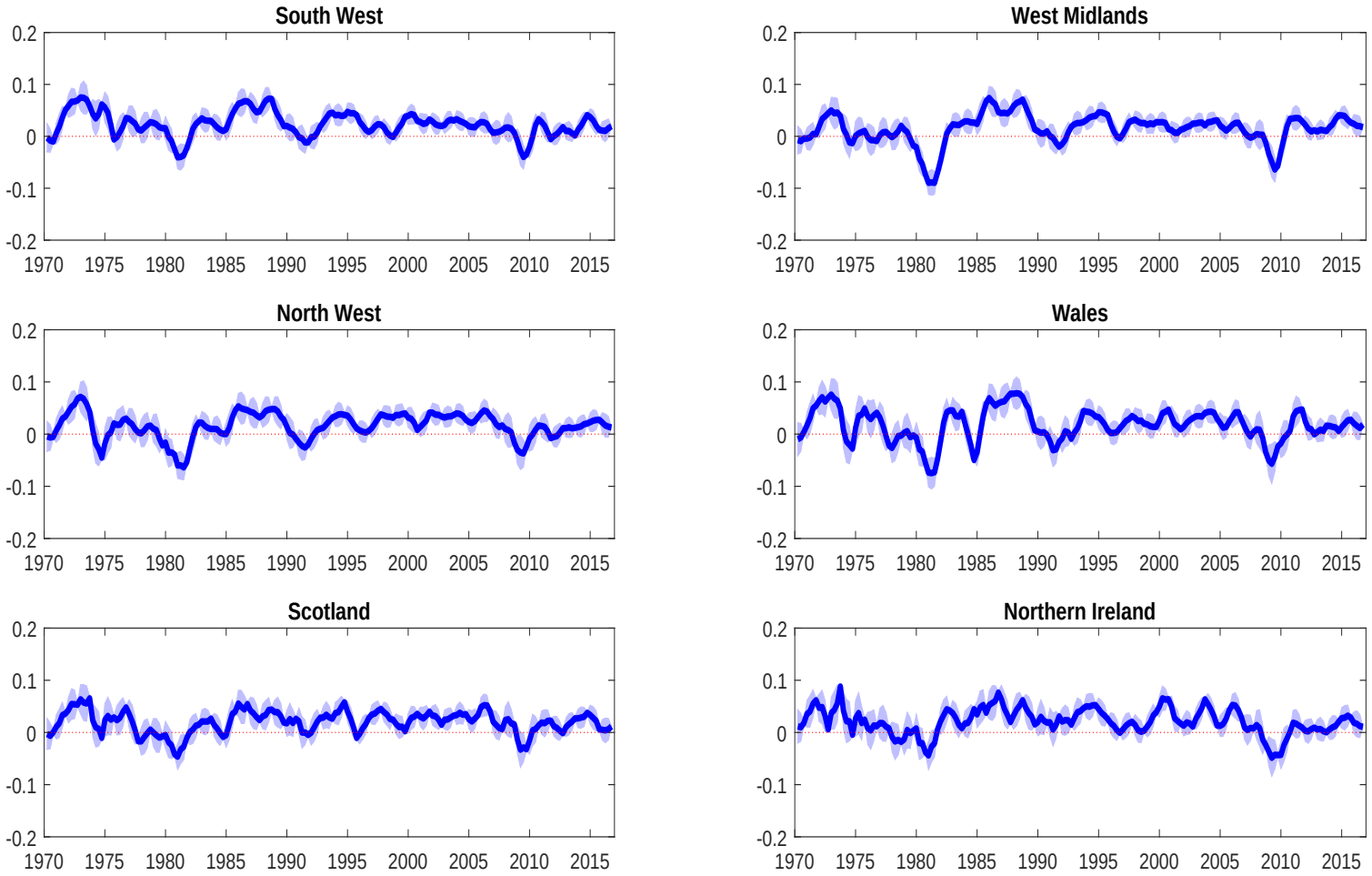


Empirical Results - Real GVA

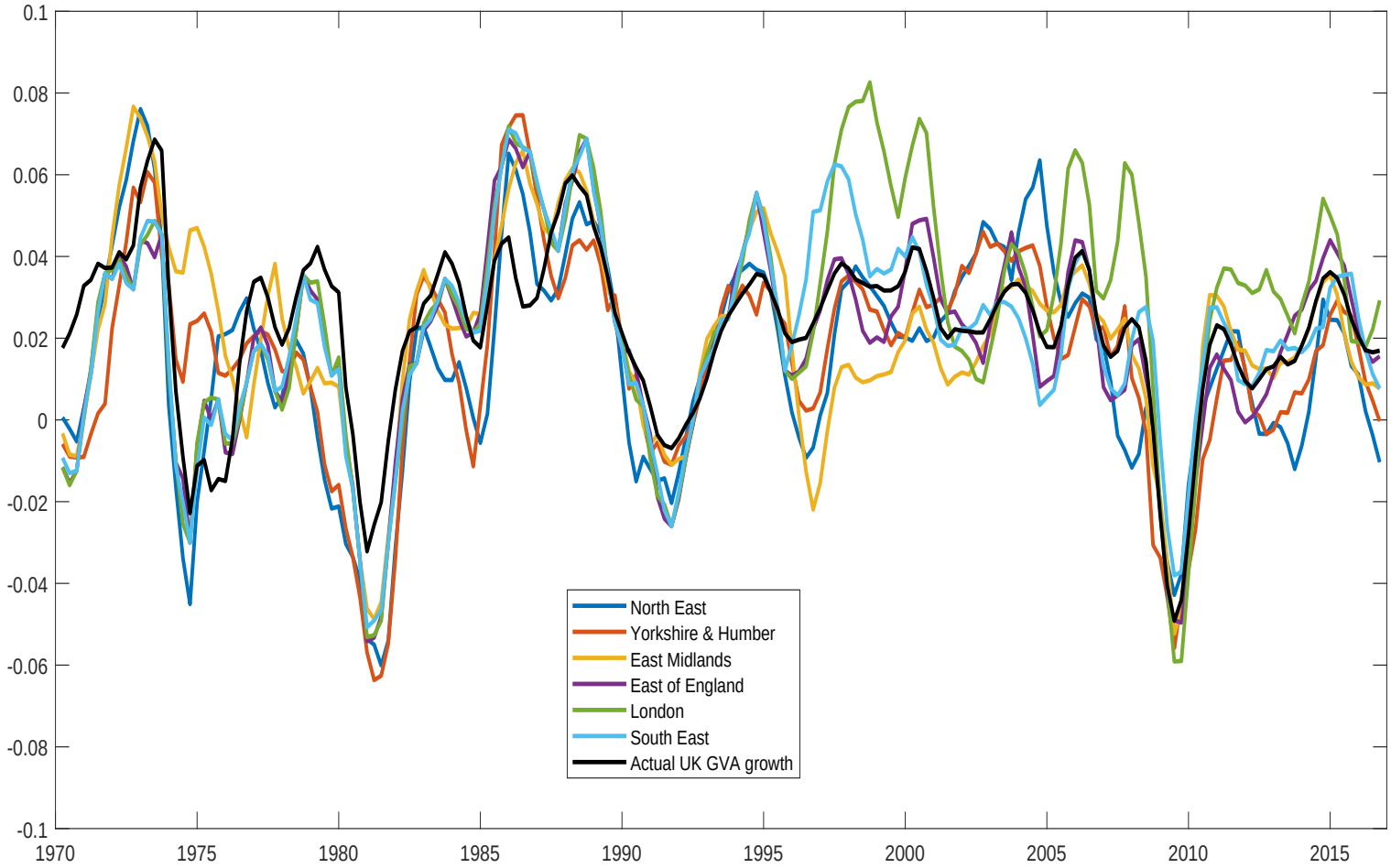
Annualised growth rates



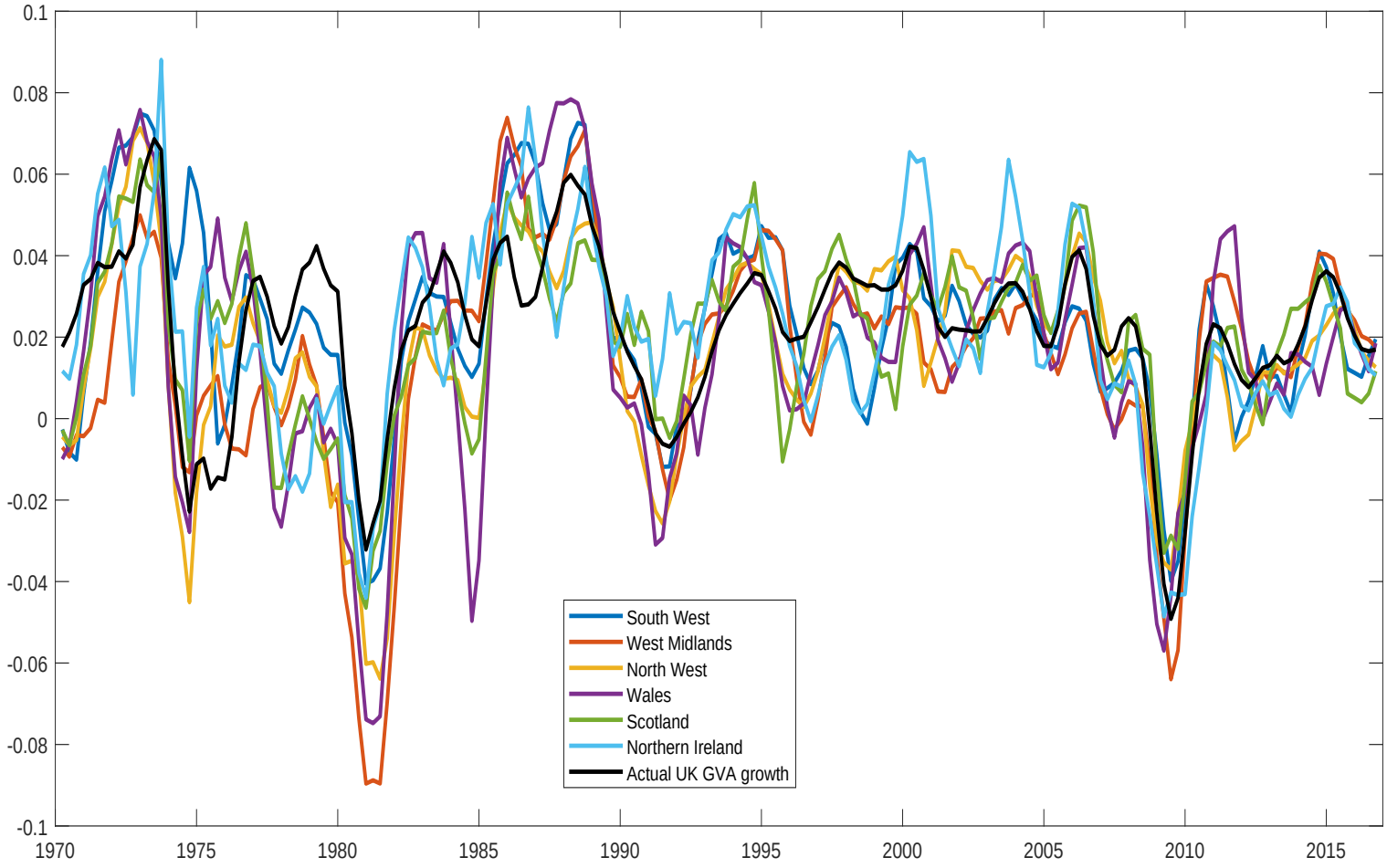
Empirical Results - Real GVA



Empirical Results - Real GVA



Empirical Results - Real GVA



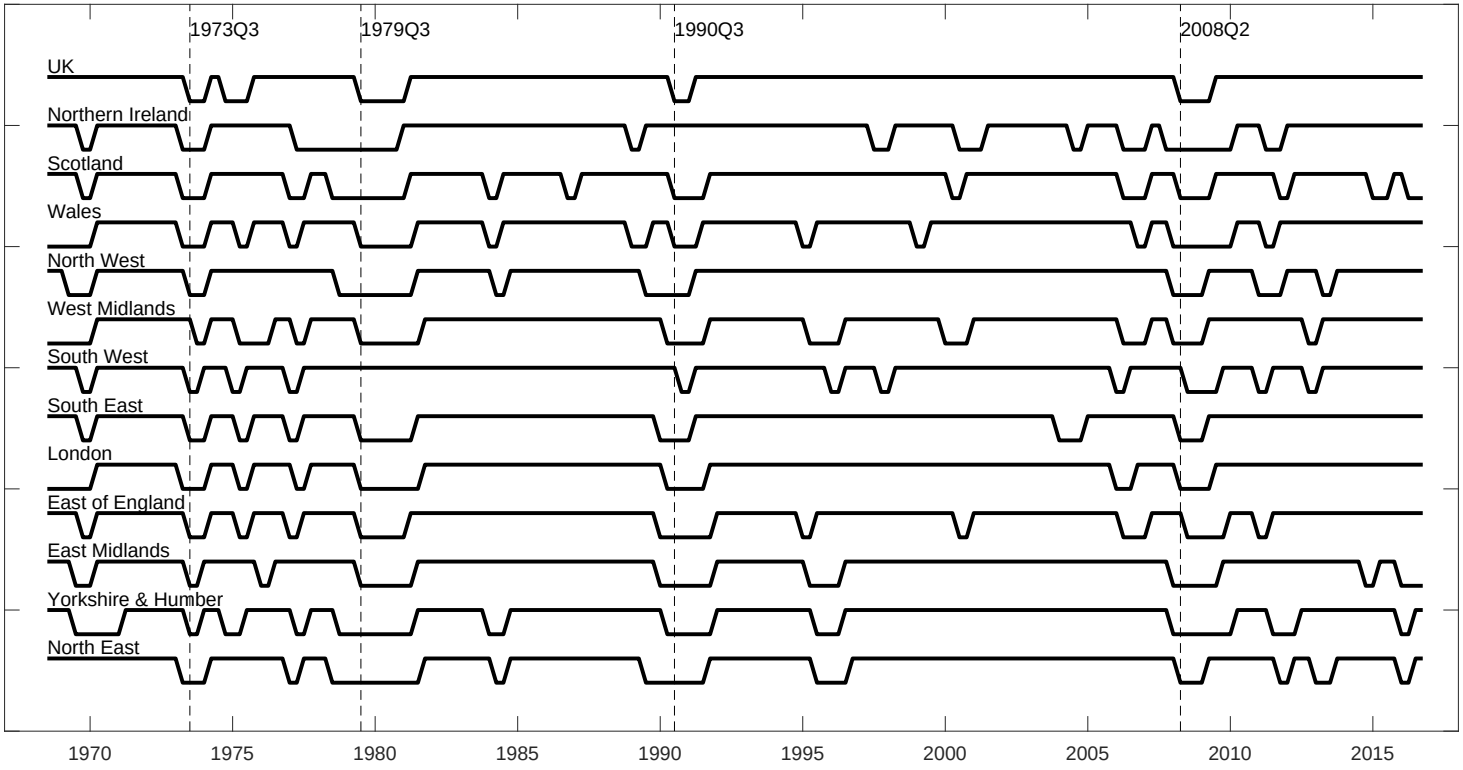
Empirical Results - Real GVA

Business cycles analysis - Harding and Pagan (2002) JME paper

	Durations (quarters)	
	Contractions	Expansion
North East	4.600	14.111
Yorkshire & Humber	4.909	13.400
East Midlands	4.625	18.625
East of England	3.636	12.700
London	4.429	18.000
South East	3.750	18.286
South West	2.273	14.900
West Midlands	4.400	12.800
North West	4.750	20.000
Wales	3.500	10.333
Scotland	3.750	11.750
Northern Ireland	4.900	13.333
UK	4.400	30.500

Empirical Results - Real GVA

Business cycles analysis - Harding and Pagan (2002) JME paper



Empirical Results - Connectedness

1. Connectedness measure of Diebold and Yilmaz (2014) JOE.
2. Construct forecast error variance decompositions $d_{i,j}^h$ for $i,j = 1,..,n$ and $h = 1,..,H$
3. Proportion of the h-step ahead forecast error for region i which is accounted for by the errors in the equation for region j
4. We use generalized variance decomposition
5. Total connectedness FROM other regions to region i at horizon h is
$$\sum_{j \neq i} d_{i,j}^h$$
6. Measure of how information in other regions impacts the forecast error variance of region i
7. Call this "connectedness from" measure
8. "Connectedness to" is
$$\sum_{i \neq j} d_{i,j}^h$$

Empirical Results - Connectedness

1. Our connectedness measures are at the quarterly frequency
2. $h = 1$ measure connectedness in terms of the one quarter ahead forecast error variances
3. These could not have been produced using VAR with annual data
4. We can compute a connectedness measure for each point of time
5. Substantial variation across regions
6. Substantial differences between To and From
7. Even at very short ($h = 1$) horizon large amount of connectedness
8. At longer horizons ($h = 20$) connectendess measures rise.

Empirical Results - Connectedness

Connectedness table for Real GVA at 2016Q4

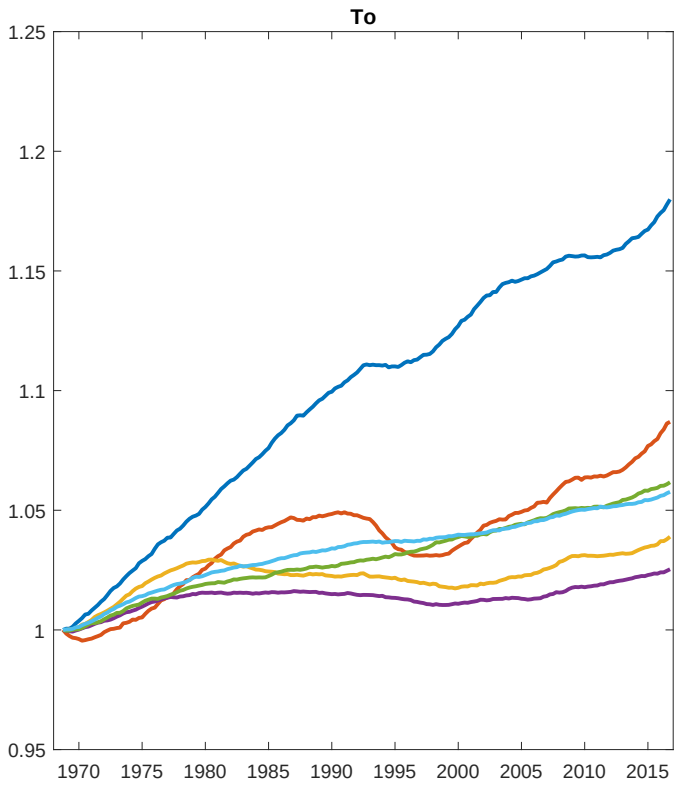
	From h=1	To h=1	From h=20	To h=20
UK	31%	8%	79%	67%
Inflation	22%	6%	70%	25%
Interest Rate	21%	6%	71%	28%
Exchange Rate	29%	24%	78%	56%
Oil	29%	85%	81%	149%
North East	28%	18%	88%	61%
Yorkshire and The Humber	22%	16%	88%	54%
East Midlands	37%	31%	88%	72%
East of England	35%	41%	84%	100%
London	27%	30%	84%	83%

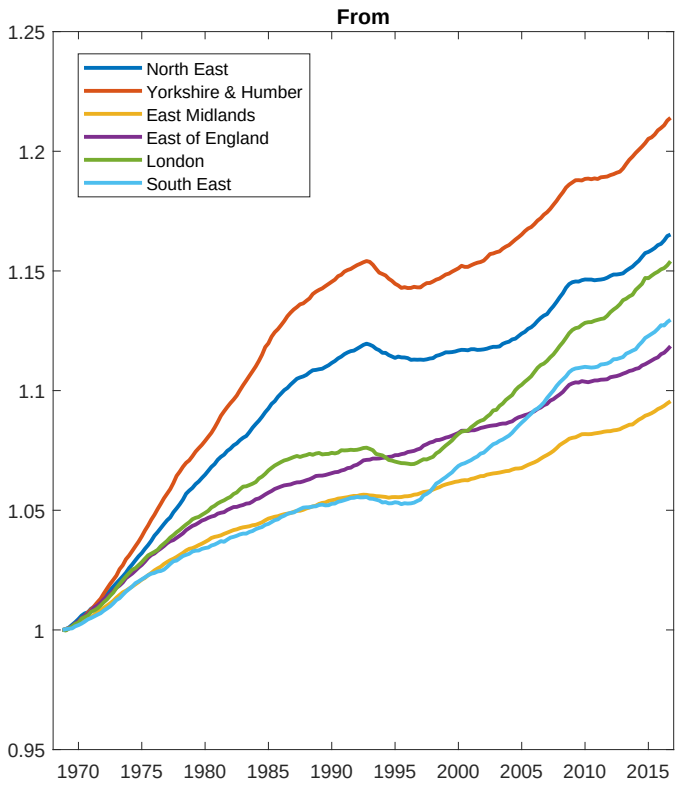
Empirical Results - Connectedness

Connectedness table for Real GVA at 2016Q4

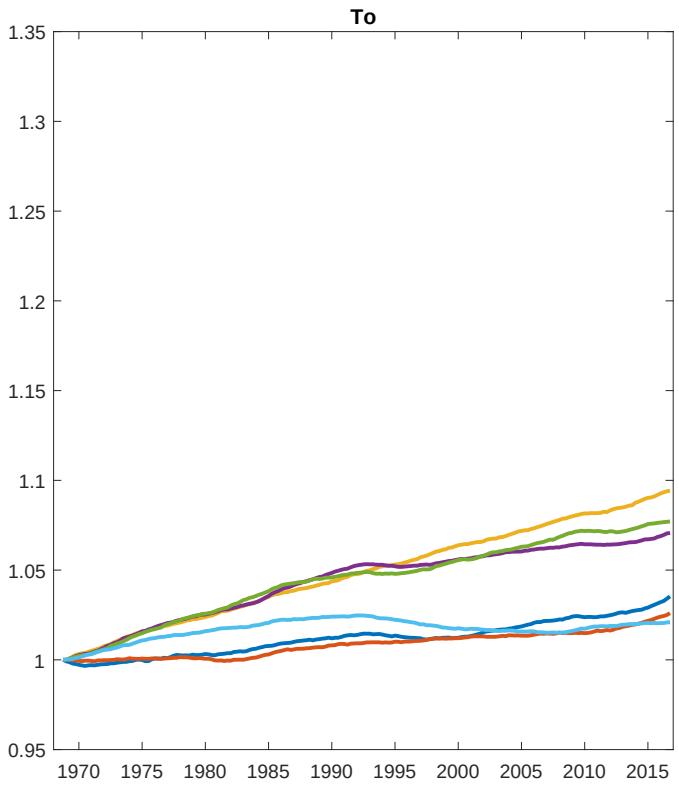
	From h=1	To h=1	From h=20	To h=20
South East	31%	26%	87%	72%
South West	28%	23%	86%	68%
West Midlands	26%	20%	85%	70%
North West	32%	35%	80%	117%
Wales	30%	46%	77%	137%
Scotland	28%	32%	80%	106%
Northern Ireland	25%	39%	78%	118%

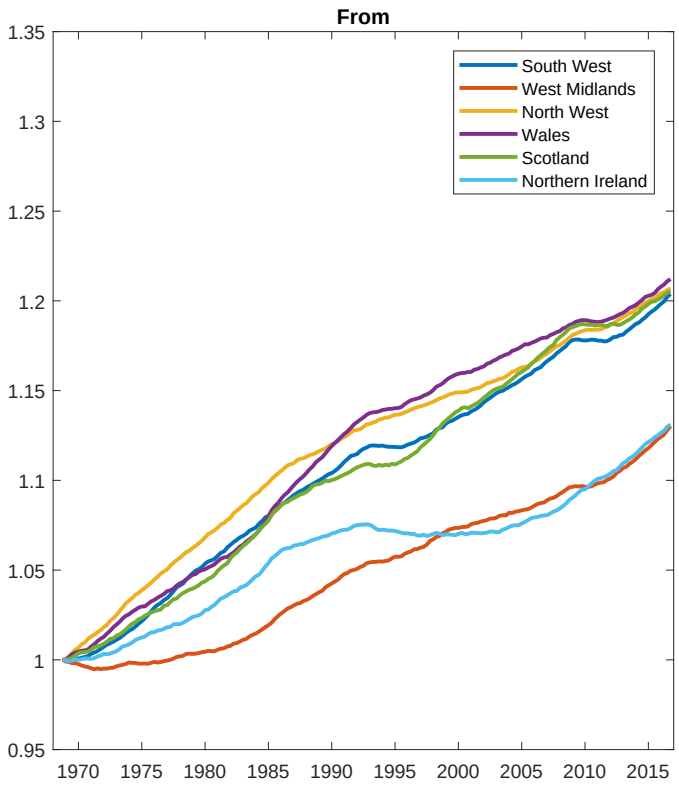
Connectedness over time - $h = 1$ quarter ahead



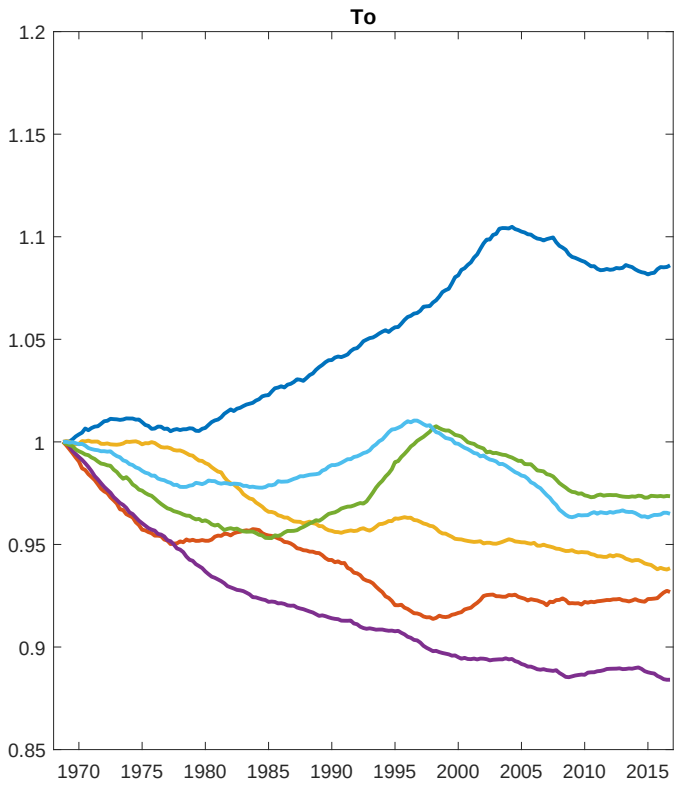


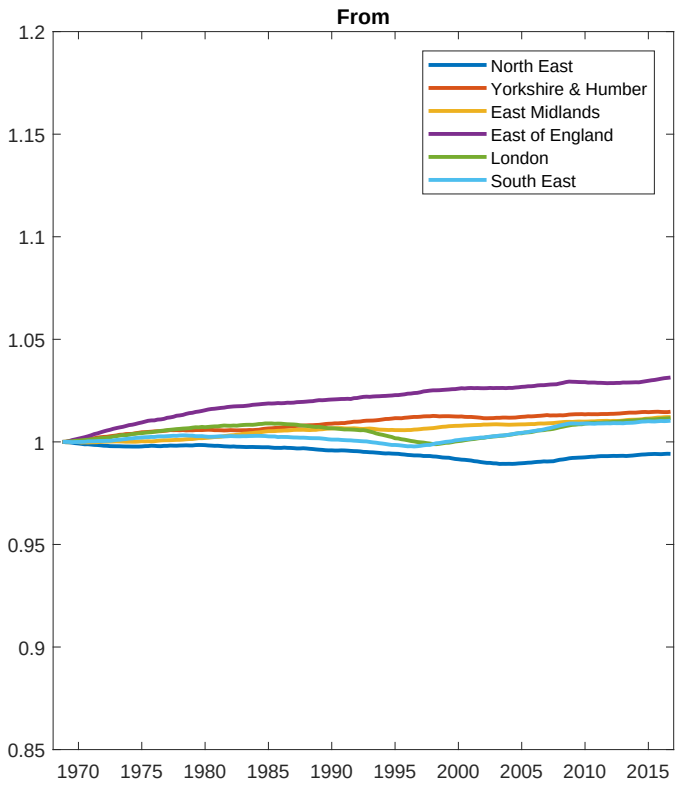
Connectedness over time - $h = 1$ quarter ahead





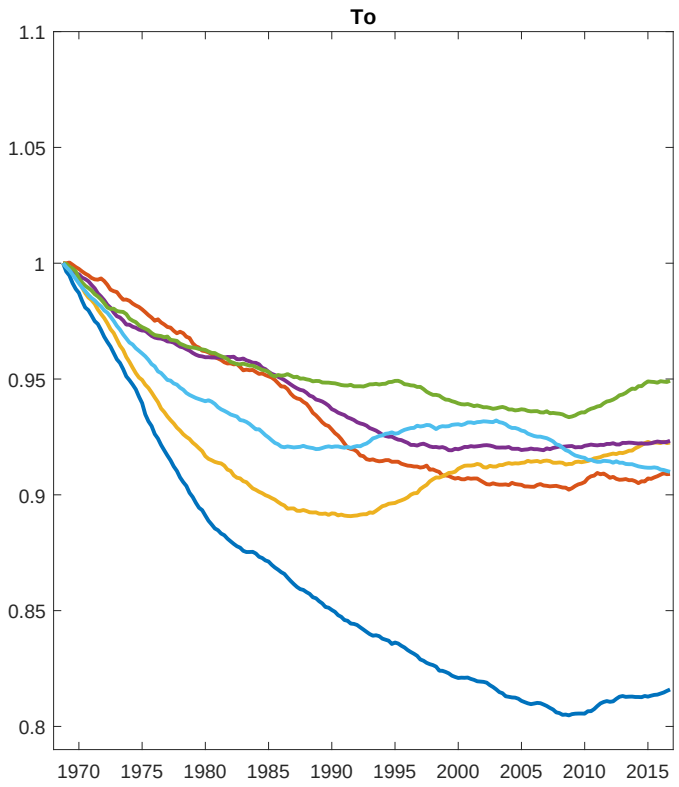
Connectedness over time - $h = 20$ quarter ahead

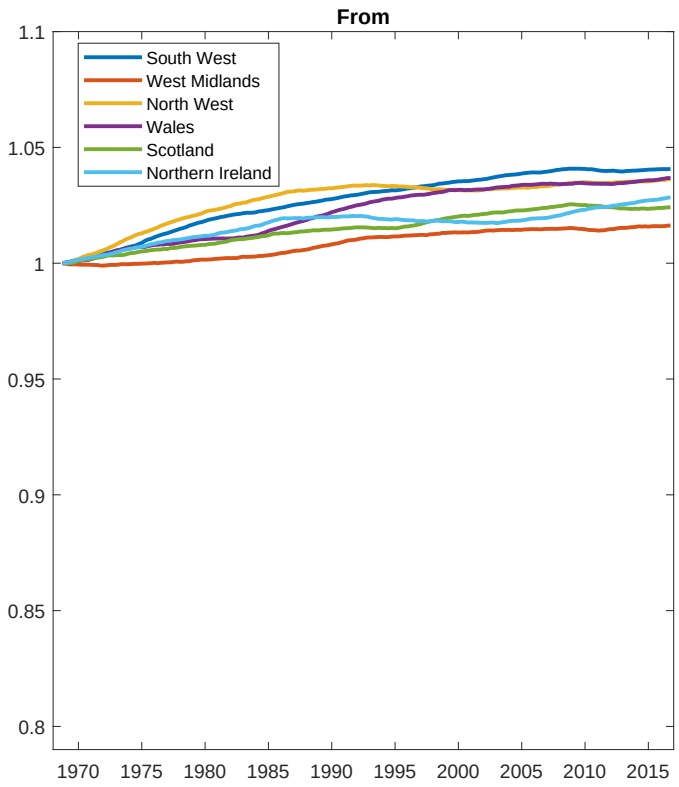




Empirical Results - Connectedness

Connectedness over time - $h = 20$ quarter ahead





Forecasting

- Nominal GVA
- Real Time forecasting.
- Forecasting evaluation period: 2000-2015.

RMSFE	MF-VAR-SV	AR(1)
North East	**0.058**	0.134
Yorkshire & Humber	**0.052**	0.133
East Midlands	**0.057**	0.136
East of England	**0.062**	0.142
London	**0.073**	0.139
South East	**0.063**	0.137
South West	**0.061**	0.136
West Midlands	**0.054**	0.133
North West	**0.064**	0.133
Wales	**0.064**	0.134
Scotland	**0.056**	0.133
Northern Ireland	**0.076**	0.140

Forecasting (cont.)

Log scores	MF-VAR-SV	AR(1)
North East	**1.396**	0.559
Yorkshire and The Humber	**1.442**	0.559
East Midlands	**1.391**	0.548
East of England	**1.253**	0.524
London	**1.087**	0.534
South East	**1.251**	0.542
South West	**1.285**	0.543
West Midlands	**1.324**	0.563
North West	**1.175**	0.559
Wales	**1.110**	0.555
Scotland	**1.203**	0.561
Northern Ireland	**1.020**	0.522

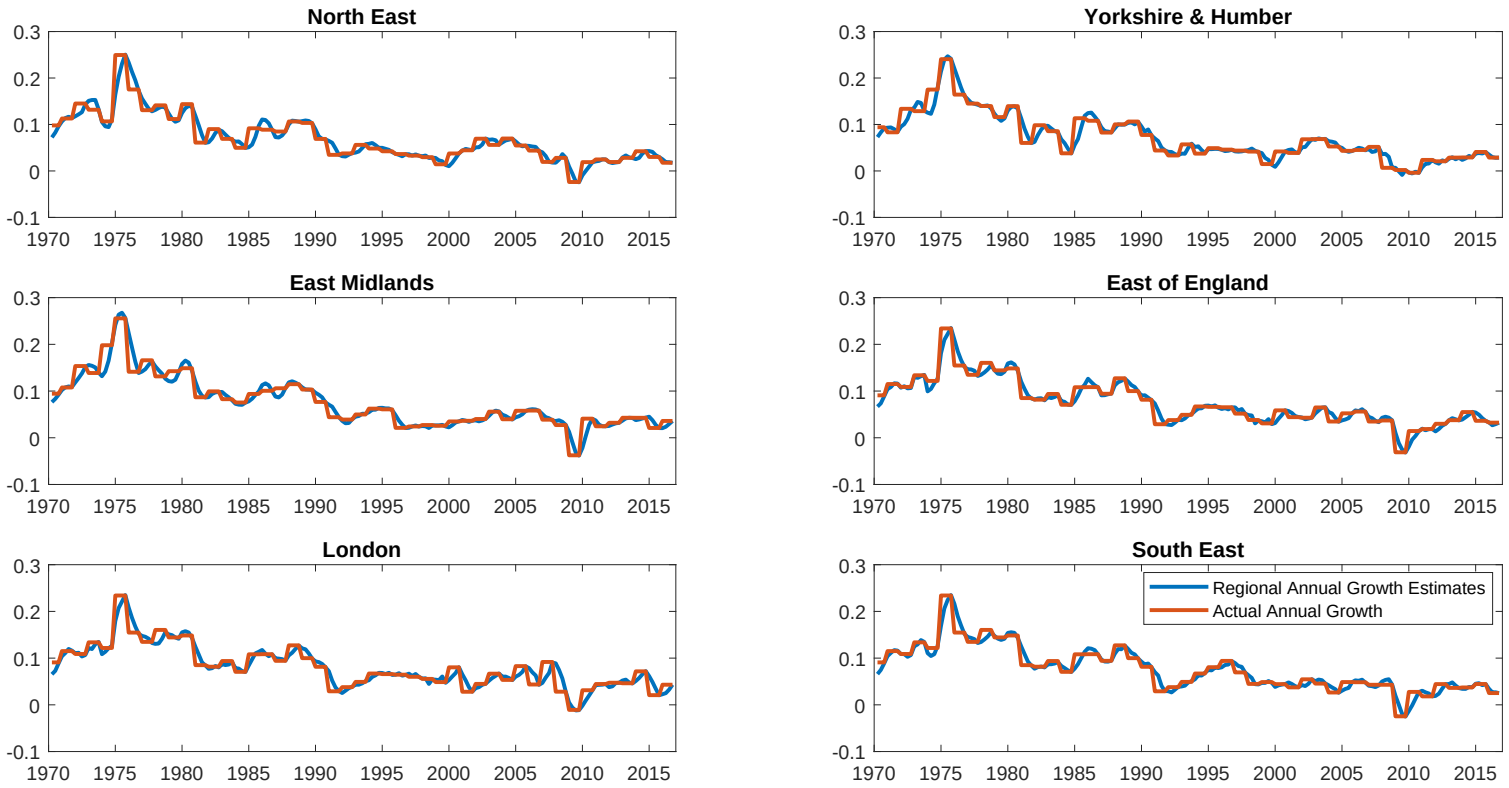
Conclusion

- MF-VAR-SV with Dirichlet-Laplace prior works well for producing quarterly regional estimates.
- Historical quarterly regional GVA growth estimates are useful in and of themselves. e.g Business cycle analysis
- Also useful to examine (high frequency) connectedness between regions and macro variables.
- MF-VAR-SV provides good forecasts.
- Extension: Estimate both Nominal and Real GVA jointly.

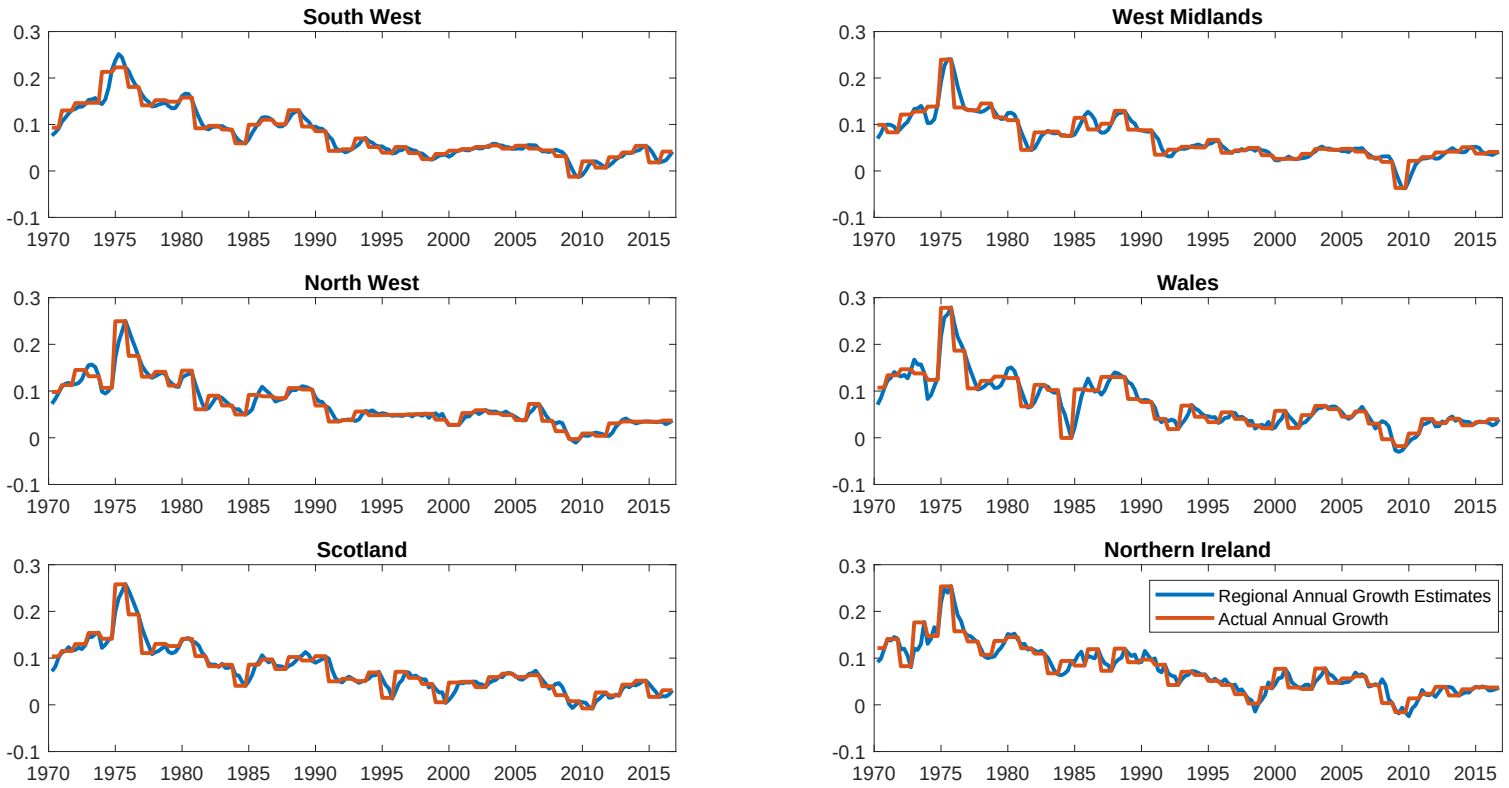
Paper details

- Access: Economic Statistics Centre of Excellence Discussion papers series
  - https://www.escoe.ac.uk/research/discussion-papers/
- Current UK nowcasts
  - https://www.escoe.ac.uk/regionalnowcasting/

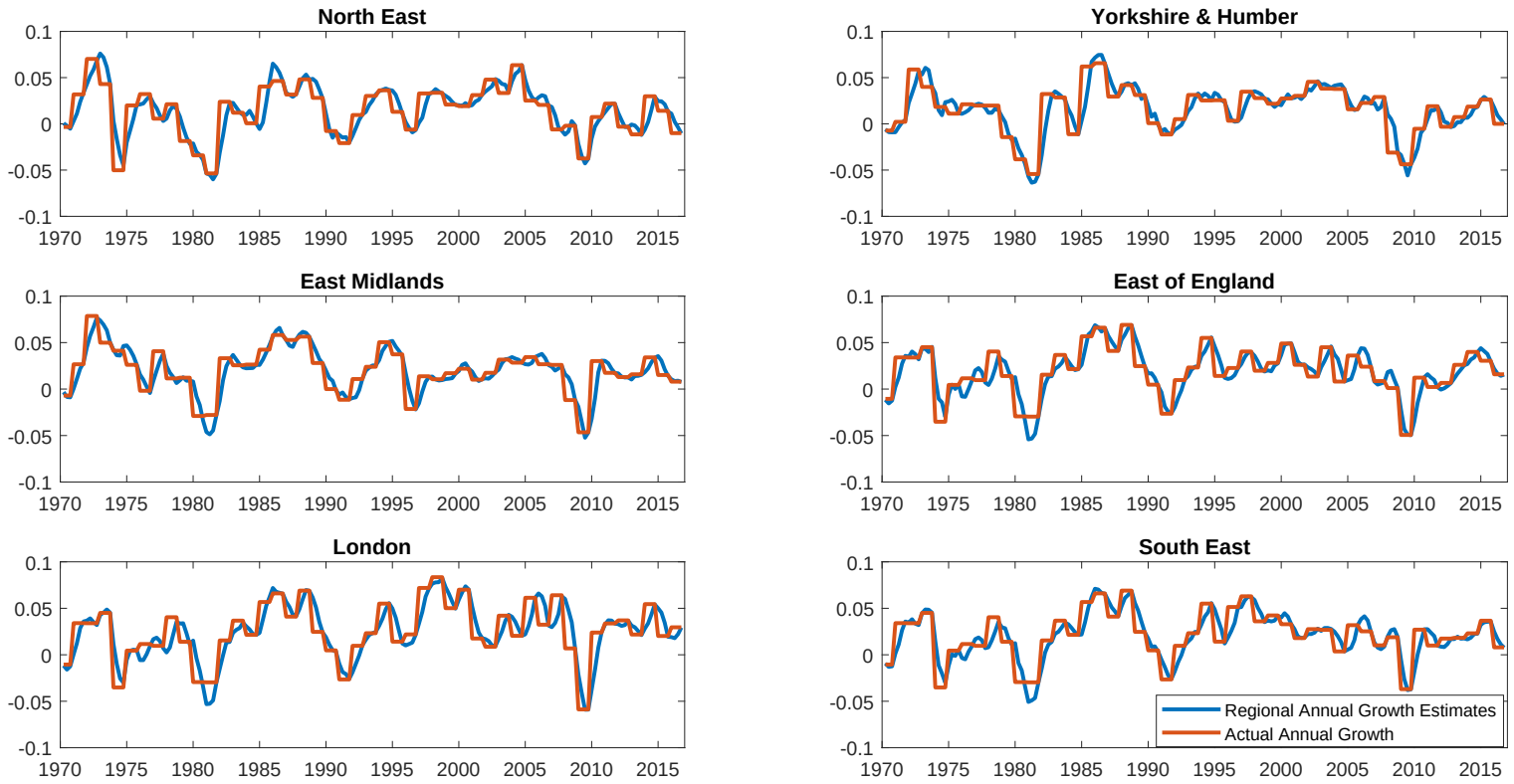
Actual Vs Estimates



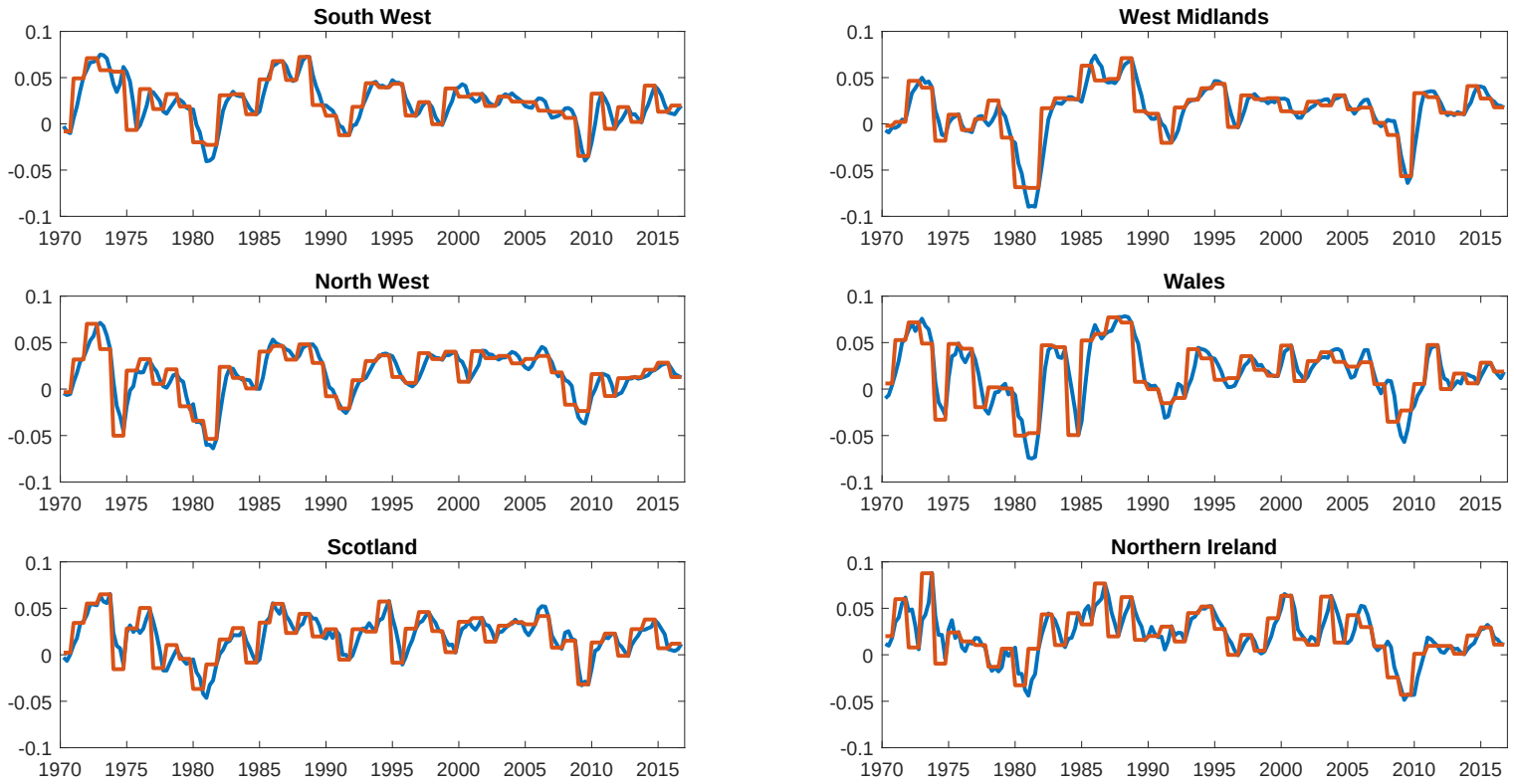
Actual Vs Estimates



Actual Vs Estimates



Actual Vs Estimates



Scotland comparison