Spatial econometrics: a critical review with reference to dynamic spatial panel models and the EU regional economies

Bernard Fingleton
Department of Land Economy
University of Cambridge

Paper presented at the 36th Annual conference of the Italian Regional Science Association, Cosenza, Italy

Spatial econometrics: a critical review with reference to dynamic spatial panel models and the EU regional economies

- This paper takes a constructively critical view of spatial econometrics
- focussing on the advantages of a dynamic spatial panel modelling approach
- The paper acknowledges that various criticisms have been made of spatial econometrics
- and shows how the model approach adopted provides a response to some of these
- simulations highlight fundamental contrasts between prospective employment levels in core and periphery regions of the EU.

Critique of econometrics

- ‘black magic’ and ‘statistical alchemy’ …. Keynes (1940)
- ‘Let’s take the con out of Econometrics’… Lemer(1983)
- ‘serious doubts’ ….Pesaran(1990)
- ‘econometrics is subject to serious limitations, which stem largely from the incompleteness of economic theory and the non-experimental nature of economic data’ ….Pesaran(1990)

Critique of spatial econometrics

- ‘spatial econometrics is typically applied in a mechanical fashion, variables are introduced simply because they are significant, without a priori rationale’
- ‘spatial econometricians often work in isolation from urban economists and other regional scientists’
- ‘overall there is a lack of theoretical justification for variables that characterize spatial econometric models’

Corrado & Fingleton (2011)

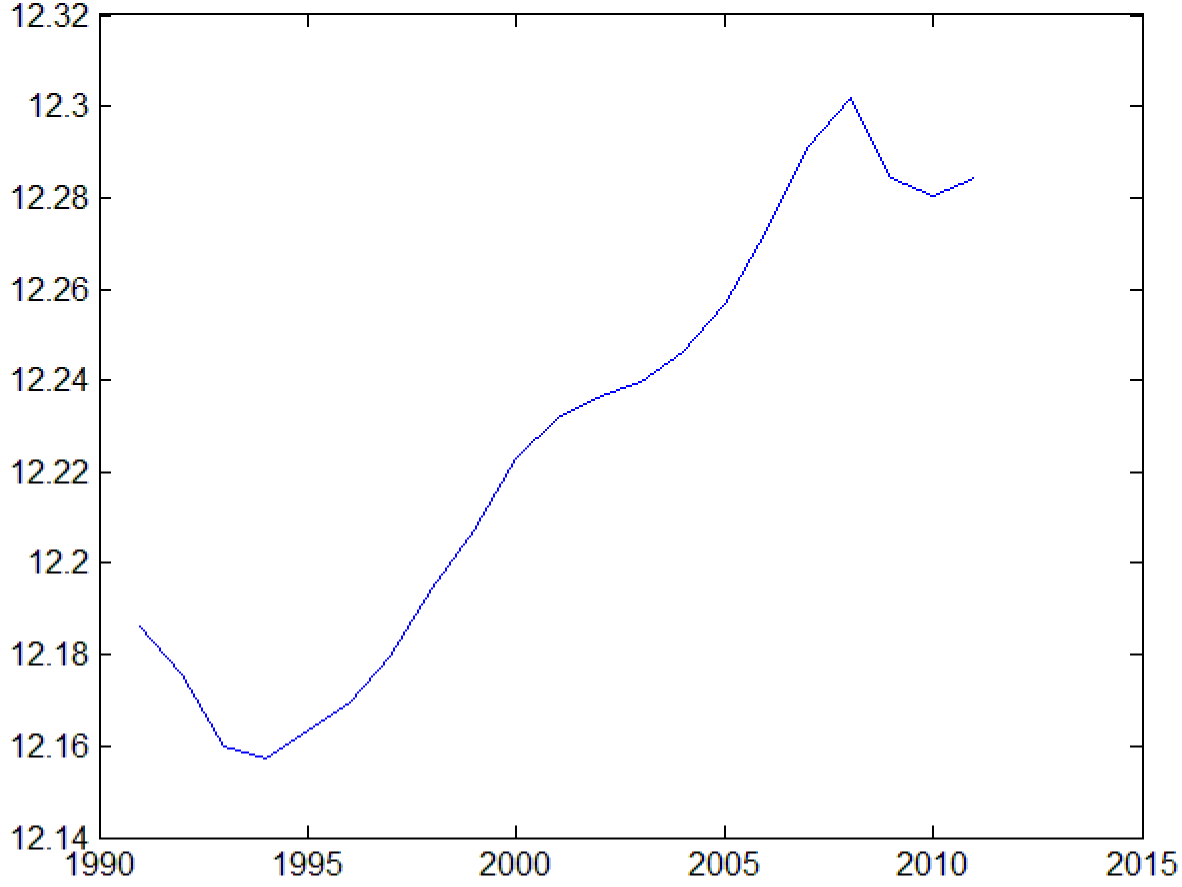
Critique of spatial econometrics

- many spatial econometrics papers are solely about technique
- papers published in high-status journals that do not attempt to fit models to real data, relying solely on Monte Carlo simulation
- by not demonstrating the methodology using real data, some of the practical considerations that applied workers face are not being addressed

Aim of the paper

- In this paper I attempt to use the model with real data to say something about the post-2007 crisis of employment in European regions
- The question is, what has to happen to the drivers of employment to recover the situation back to the 2007 peak? To do this we need a model.

Figure 1: Aggregate log EU employment



Features of the modelling approach

- In this paper we describe the state of the art in econometric methodology, namely dynamic spatial panel modelling
    - due to Baltagi, Fingleton and Pirotte(2015)
- apply it to a substantive problem, prediction of employment levels across the EU regions under different scenarios
- Innovative aspects
    - Dynamic model with BOTH endogenous spatial lag and spatial error process
    - Spatial moving average (SMA) errors not SAR
    - Estimation robust to endogeneity allowing causal interpretation
    - Novel approach to prediction & simulation of scenarios

Atheoretical model

$$y_{it} = \gamma y_{it-1} + \rho_1 \sum_{j=1}^{N} w_{ij} y_{jt} + \rho_2 \sum_{j=1}^{N} w_{ij} y_{jt-1} + x_{it}\beta_1 + \sum_{j=1}^{N} w_{ij} x_{jt}\beta_2 + \ldots$$

$$x_{it-1}\beta_3 + \sum_{j=1}^{N} w_{ij} x_{it-1}\beta_4 + \varepsilon_{it}$$

$$\varepsilon \sim iid(0, \sigma_\varepsilon^2)$$

Purely inductive approach, variables included if significant, with no theoretical provenance

Features of the modelling approach

- Advantages
  - Specification informed by theory
  - Panel approach
  - Spatial interaction motivated by data
  - Estimation robust
  - Causal interpretation possible

advantages of panel data modelling

- Controls for individual heterogeneity
  - in the regional context, we wish to avoid the drivers of employment simply picking up unobserved and unmodelled time-constant regional characteristics
- more informative data, more variability, less collinearity, more degrees of freedom, and more efficiency
  - Combine information from between-variation (between regions) and within-variation (within regions, i.e. regions’ time series)

Fundamental variables

Cobb-Douglas $$\mathbf{Q}_t = \mathbf{A}_0 \exp\left(\lambda t\right) \mathbf{K}_t^{\tilde{\alpha}} \mathbf{E}_t^{\tilde{\beta}}$$

Verdoorn Law

$$\ln \mathbf{P}_t = \left[(\tilde{\beta} - 1) / \tilde{\beta} \right] \ln \mathbf{Q}_t + \left(1/\tilde{\beta} \right) \ln \mathbf{A}'_t + \left(\tilde{\alpha}/\tilde{\beta} \right) \ln \mathbf{K}_t$$

$$\ln \mathbf{P}_t = \ln \mathbf{Q}_t - \ln \mathbf{E}_t$$

$$\ln \mathbf{E}_t = \left(1/\tilde{\beta} \right) \ln \mathbf{Q}_t - \left(1/\tilde{\beta} \right) \ln \mathbf{A}'_t - \left(\tilde{\alpha}/\tilde{\beta} \right) \ln \mathbf{K}_t$$

Econometric model

$$\mathbf{y}_t = \beta_1 \mathbf{x}_{1t} + \beta_2 \mathbf{x}_{2t} + \boldsymbol{\varepsilon}_t$$

$\mathbf{y}_t = \ln \mathbf{E}_t$ Endogenous

$\mathbf{x}_{1t} = \ln \mathbf{Q}_t$ Exogenous, predetermined or endogenous

$\mathbf{x}_{2t} = \ln \mathbf{K}_t$ Exogenous, predetermined or endogenous

The model

$$\mathbf{y}_t = \gamma \mathbf{y}_{t-1} + \rho_1 \mathbf{W}_N \mathbf{y}_t + \mathbf{x}_t \beta + \varepsilon_t$$

$\mathbf{y}_{t-1}$ Represents the effect of previous (log) employment level on current employment,
can be thought of as the impact of market imperfections,
which cause employment to react non-instantaneously to changes in (the drivers of) employment

‘ it may take time for new capital to function effectively, or for extra labour to be properly assimilated into the technology and working practices of employers’

(Fingleton, Garretson and Martin, 2015)

The model

$$\mathbf{y}_t = \gamma \mathbf{y}_{t-1} + \rho_1 \mathbf{W}_N \mathbf{y}_t + \mathbf{x}_t \beta + \varepsilon_t$$

$\mathbf{W}_N \mathbf{y}_t$

core issue of spatial econometrics
on what basis is spatial matrix constructed?
how can the spatial lag be justified?
need for a greater theoretical basis, but not an easy task

One way forward is to base the matrix on some empirically observable measures of interaction between regions

Here use inter-regional trade flows as a measure of the amount of interdependence between regions.

$$\mathbf{W}_N$$

- we only have international trade flows to work with, so interregional trade flows are imputed from these
- Gives the interregional connectivity matrix
  - See Chow and Lin (1971), Polasek, Verduras and Sellner (2010), Vidoli and Mazziotta (2010), Doran and Fingleton (2013), Fingleton, Garretsen and Martin(2015)

$$\mathbf{W}_N$$

- fit a model to the known bilateral trade flows, thus in our case we have data for aggregate trade values between 21 EU counties (t_{Nat}), thus giving 420 observations for the year 2000
- model this by country level variables, namely great circle distances (G_{Nat}) and national employment levels (E_{Nat}) in 2000 These are the means of each country's interregional distances.
- regression parameter estimates β_{Nat}, and estimated regression residuals e_{Nat}

$$\ln t_{Nat} = \left[const_{Nat} \;\; \ln G_{Nat} \;\; \ln E_{Nat} \right] \beta'_{Nat} + e_{Nat}$$

$$\mathbf{W}_N$$

- obtain regional bilateral trade flows (t_{Reg}) by applying the estimated β_{Nat} to the same variables (G_{Reg}, E_{Reg}) measured at the regional level
- and adding an equal share of national level residuals to each region within a country

$$\ln t_{\mathrm{Re}g} = \left[const_{\mathrm{Re}g} \quad \ln G_{\mathrm{Re}g} \quad \ln E_{\mathrm{Re}g} \right] \hat{\beta}'_{Nat} + VD'(DVD')^{-1}\hat{e}_{Nat}$$

$$\mathbf{W}_N \mathbf{y}_t$$

- critics suggest that the spatial lag is in reality a fiction
  - justifying its presence as a result of statistical significance may be misleading
  - it may be simply picking up the effects of omitted spatially dependent variables
- Is the spatial lag masquerading as other omitted effects?

$$\mathbf{W}_N \mathbf{y}_t$$

- Here attempt to control for omitted variables
  - By the panel approach
    - allows control for a host of unobserved (time-invariant) individual (regional) effects, thus reducing the possibility of omitted variable bias
  - By the presence of a spatially dependent error process
    - controlling for omitted spatially autocorrelated variables, which otherwise would be picked up by the endogenous spatial lag

$$\mathbf{W}_N \mathbf{y}_t$$

Leontieff expansion

$$\mathbf{y}_t = \rho_1 \mathbf{W_N} \mathbf{y}_t + \mathbf{x}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

$$\mathbf{y}_t = (\mathbf{I_N} - \rho_1 \mathbf{W_N})^{-1} (\mathbf{x}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t)$$

$$\mathbf{y}_t = \left(\sum_{i=0}^{\infty} \rho_1^i \mathbf{W}_N^i \right) \mathbf{x}_t \boldsymbol{\beta} + \left(\sum_{i=0}^{\infty} \rho_1^i \mathbf{W}_N^i \right) \boldsymbol{\varepsilon}_t$$

$$\mathbf{y}_t = \mathbf{x}_t \boldsymbol{\beta} + \rho_1 \mathbf{W}_N \mathbf{x}_t \boldsymbol{\beta} + \rho_1^2 \mathbf{W}_N^2 \mathbf{x}_t \boldsymbol{\beta} + \rho_1^3 \mathbf{W}_N^3 \mathbf{x}_t \boldsymbol{\beta} + \ldots.$$

the drivers of employment in other importing regions, namely output and capital, affect the level of employment in the exporting region

Likewise unobservable shocks to the importing regions will also affect the level of employment in the exporting region

SMA errors

$$\varepsilon_{it} = u_{it} - \rho_2 \mathbf{m}_i \mathbf{u}_t \qquad \mathbf{m}_i = (m_{i1}, \ldots, m_{iN})$$ is i'th row of $\mathbf{M}_N$

$\mathbf{M}_N$ standardised N by N contiguity matrix

a shock to the error at location will only affect directly interacting regions , rather than the complex interdependence implied by a SAR error process

(see Fingleton, 2008a,b, Baltagi, Bresson and Pirotte, 2012, Baltagi, Fingleton and Pirotte, 2015)

Compound errors

$$u_{it} = \mu_i + \nu_{it} \qquad \mu_i \sim iid(0, \sigma_\mu^2) \qquad \nu_i \sim iid(0, \sigma_\nu^2)$$

unit-specific component imparts time dependency to the error process
and accounts for spatially autocorrelated inter-locational heterogeneity

estimation

Differencing 'kills' the time-invariant unobserved individual effects, which are correlated with the spatial lag and the time-lagged dependent variable

$$\Delta \mathbf{y}_t = \gamma \Delta \mathbf{y}_{t-1} + \rho_1 \mathbf{W}_N \Delta \mathbf{y}_t + \beta_1 \Delta \mathbf{x}_{1t} + \beta_2 \Delta \mathbf{x}_{2t} + \Delta \boldsymbol{\varepsilon}_t$$

this leads to orthogonality conditions and hence valid instruments,
which are levels of the endogenous and explanatory variables
which are uncorrelated with the differenced errors

The basic idea goes back to Arellano and Bond(1991)

but given the presence of the spatial lag in our model, the approach adopted
is based on an extension of the Arellano and Bond(1991) estimator for dynamic panels

The extension introduces spatial instruments combined with the usual non-spatial instruments leading to consistent parameter estimates.

estimation

$$\Delta \mathbf{y}_t = \gamma \Delta \mathbf{y}_{t-1} + \rho_1 \mathbf{W}_N \Delta \mathbf{y}_t + \beta_1 \Delta \mathbf{x}_{1t} + \beta_2 \Delta \mathbf{x}_{2t} + \Delta \boldsymbol{\varepsilon}_t$$

regressor exogeneity
the assumption is that the regressors are uncorrelated with all past, present and future errors

regressors are predetermined
Regressors contemporaneously uncorrelated with the errors but are correlated with errors at t-1 and earlier

Regressor endogeneity
regressors at time t are correlated with current and past errors
In other words, output and capital at time t both affect, and are affected by, employment at time t.

estimation

Given an assumption that the errors are serially uncorrelated

Moments conditions assuming endogeneity of regressors

$$E(y_{il}\Delta \nu_{it}) = 0 \qquad \forall i, l = 0,1,2,\ldots,t-2; t = 2,\ldots,T$$

$$E(x_{k,im}\Delta \nu_{it}) = 0 \qquad \forall i, k, m = 1,\ldots,t-2, t = 3,\ldots,T$$

$$E(\sum_{i\neq j} w_{ij} y_{jl}\Delta \nu_{it}) = 0 \qquad l = 0,\ldots,t-2; t = 2,\ldots,T$$

$$E\sum_{i\neq j} w_{ij} x_{k,jm}\Delta \nu_{it}) = 0 \qquad \forall i, k, m = 1,\ldots,t-2; t = 3,\ldots T$$

estimation

- Thus if we lag endogenous variables by 2 periods we can use them as instruments
- Include spatial lags, thus extending the standard orthogonality conditions of Arellano and Bond (1991)
    - Bouayad-Agha and Védrine(2010)Baltagi, Fingleton and Pirotte (2014, 2015), Arellano and Bond(1991)

estimation

$$\Delta\mathbf{y}_t = \gamma\Delta\mathbf{y}_{t-1} + \rho_1\mathbf{W}_N\Delta\mathbf{y}_t + \beta_1\Delta\mathbf{x}_{1t} + \beta_2\Delta\mathbf{x}_{2t} + \Delta\boldsymbol{\varepsilon}_t$$

1. Instruments provide consistent estimates of $\gamma, \rho_1, \beta_1, \beta_2$

$$\varepsilon_{it} = u_{it} - \rho_2\mathbf{m}_i\mathbf{u}_t \qquad \mu_i \sim iid(0, \sigma_\mu^2) \qquad \nu_i \sim iid(0, \sigma_\nu^2)$$

2. This leads to estimates of errors and therefore GM estimates of $\rho_2, \sigma_\mu^2, \sigma_\nu^2$

solve sample moments using nonlinear least squares

3. Further steps leading to final estimates of $\gamma, \rho_1, \beta_1, \beta_2$

(Fingleton(2008a,b) , Baltagi, Fingleton & Pirotte, 2015)

Why IV/GMM not ML?

- ‘Different assumptions about the nature of the initial conditions will lead to different likelihood functions’ (Bond, 2002)
- ML estimators ‘can be inconsistent when this initial conditions process is mis-specified’(Bond, 2002)
- ML makes significant computational demands as N becomes large (Kapoor et al. 2007)
- ML models as evident in the current literature typically do not include BOTH a spatial lag and the SMA (or SAR) error process
- Single equation ML models assume exogeneity of regressors

Table 1: Parameter Estimates

		Exogenous $\mathbf{x}_{1t}, \mathbf{x}_{2t}$			Endogenous $\mathbf{x}_{1t}, \mathbf{x}_{2t}$		
variable	parameter	Param. Est.	Standard error	t ratio	Param. Est.	Standard error	t ratio
$\mathbf{y}_{t-1} = \ln \mathbf{E}_{t-1}$	γ	0.6710	0.002119	316.6	0.5183	0.01563	33.16
$\mathbf{W}_N \mathbf{y}_t = \mathbf{W}_N \ln \mathbf{E}_t$	ρ_1	0.1538	0.004189	36.7	0.4669	0.02836	16.46
$\mathbf{x}_{1t} = \ln \mathbf{Q}_t$	β_1	0.1068	0.0008956	119.2	0.02801	0.008659	3.235
$\mathbf{x}_{2t} = \ln \mathbf{K}_t$	β_1	0.01719	0.0001772	97.0	0.02586	0.002939	8.8
	ρ_2	-0.4138			-0.1878		
	σ^2_μ	0.0359			0.1395		
	σ^2_υ	0.0003			0.0004		

Dynamic stability and stationarity conditions

$$(\mathbf{I}_N - \rho_1 \mathbf{W}_N), (\mathbf{I}_N - \rho_2 \mathbf{M}_N)$$ Parameter space defined so that nonsingular

$r_{\min}, \tilde{r}_{\min}$ Most negative purely real characteristic root $\mathbf{W}_N, \mathbf{M}_N$

$r_{\max}, \tilde{r}_{\max} = 1$ Assuming row standardisation of $\mathbf{W}_N, \mathbf{M}_N$

$$1/r_{\min} < \rho_1 < 1/r_{\max} \qquad -7.1851 < \hat{\rho}_1 < 1$$

$$1/\tilde{r}_{\min} < \rho_2 < 1/\tilde{r}_{\max} \qquad -1.1239 < \hat{\rho}_2 < 1$$

$$|\gamma| < 1 \qquad \hat{\gamma} = 0.5183$$

$$|\gamma| < 1 - \rho_1 r_{\max} \qquad \rho_1 > 0 \qquad |\hat{\gamma}| < 1 - \hat{\rho}_1 r_{\max} = 0.53311$$

Interpretation of estimates, $\frac{\partial y}{\partial x_k} \neq \beta_k$

- Parameter estimates per se are misleading elasticities, since not true change in dependent variable for a 1% change in a regressor
- Take spillovers into account to obtain true derivates
- But these are unhelpful for simulating medium term effects

Short-run effects

$$\begin{bmatrix} \dfrac{\partial y_1}{\partial x_{1k}} & . & \dfrac{\partial y_1}{\partial x_{Nk}} \\ . & . & . \\ \dfrac{\partial y_N}{\partial x_{1k}} & . & \dfrac{\partial y_N}{\partial x_{Nk}} \end{bmatrix}_t = \left(\mathbf{I}_N - \rho_1 \mathbf{W_N}\right)^{-1} \begin{bmatrix} \beta_k & . & 0 \\ . & \beta_k & . \\ 0 & . & \beta_k \end{bmatrix} \tag{11}$$

Instantaneous responses of employment to 1% change at time t in regressor *k*
In each of the NUTS 2 regions

Direct effect : mean of the main diagonal
Indirect effect : mean of off-diagonal cells
Total effect : sum of direct and indirect effect

LeSage and Pace(2009)

Long-run effects

$$\begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & . & \frac{\partial y_1}{\partial x_{Nk}} \\ . & . & . \\ \frac{\partial y_N}{\partial x_{1k}} & . & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix} = \left((1-\gamma)\mathbf{I}_N - \rho_1 \mathbf{W}_N\right)^{-1} \begin{bmatrix} \beta_k & . & 0 \\ . & \beta_k & . \\ 0 & . & \beta_k \end{bmatrix} \qquad (12)$$

Long-run effects are the equilibrium outcomes if the change in the regressor is maintained ad infinitum.

Direct effect : mean of the main diagonal
Indirect effect : mean of off-diagonal cells
Total effect : sum of direct and indirect effect

Table 2: Short-run and long-run, direct and indirect effects (endogeneity assumption)

$\mathbf{x}_1$ (lnQ)			
β_1	0.02801		
direct (short)	0.0281	direct (long)	0.0656
indirect (short)	0.0244	indirect (long)	1.8281
total (short)	0.0525	total (long)	1.8937
$\mathbf{x}_2$ (lnK)		$\mathbf{x}_2$	
β_2	0.02586		
direct (short)	0.0259	direct (long)	0.0606
indirect (short)	0.0226	indirect (long)	1.6876
total (short)	0.0485	total (long)	1.7482

Overall the total long-run effects are much greater than the apparent causal effects of the regressors suggested by Table 1

because the passage of time has allowed the full effect of spillovers to be realised

A more useful approach

- changes in output and capital stock will have big long term effects
- assume a 1% increment to the levels occurring over the very long term
- not very informative or realistic from a policy perspective
- of more interest is the case where the shocks to the employment drivers are allowed to
  - vary over time
  - apply to the short and medium term
  - occur simultaneously in both regressors
- This extra flexibility helps visualize what kind of policy would be required to enable EU regional employment to recover to pre-crisis levels
- To see the realizations under these conditions, we apply a different, but related methodology, using prediction equation
    - Chamberlain (1984) and Sevestre and Trognon (1996), Baltagi, Fingleton and Pirotte(2011,2014)

The linear predictor : SAR/SMA errors

Following Chamberlain (1984) and Sevestre and Trognon (1996), Baltagi et al. (2014a)

$$E(y_{it}) = \gamma^t \sum_{j=1}^N h_{ij}^{(t)} y_{j0} + \sum_{l=1}^t \gamma^{l-1} \sum_{j=1}^N h_{ij}^{(l)} x_{jt-l+1}\beta + \sum_{l=1}^t \gamma^{l-1} \sum_{j=1}^N p_{ij}^{(l)} E(\mu_j)$$

This is exactly the same as

$$E(\mathbf{y}_t) = \mathbf{G}_N^{-1}(\gamma E(\mathbf{y}_{t-1}) + \mathbf{x}_t\beta + \mathbf{B}_N^{-1}E(\boldsymbol{\mu}))$$

$$E(\mathbf{y}_t) = \mathbf{G}_N^{-1}(\gamma E(\mathbf{y}_{t-1}) + \mathbf{x}_t\beta + \mathbf{B}_N E(\boldsymbol{\mu}))$$

$$\mathbf{G}_N = (\mathbf{I}_N - \rho_1 \mathbf{W}_N)$$

$$\mathbf{B}_N = (\mathbf{I}_N - \rho_2 \mathbf{M}_N)$$

prediction

- Prediction…..not easy!
  - Long run truly unknown, because model parameters may not be stable
  - Different variables may emerge that are currently dormant and unknown
  - Need to forecast regressors for out-of-sample (*ex ante*) prediction
- Within-sample (*ex post*) prediction more feasible, since regressors and dependent variable known

Prediction equation

$$\hat{\mathbf{y}}_t = \hat{\mathbf{G}}_N^{-1}\left[\hat{\gamma}\hat{\mathbf{y}}_{t-1} + \mathbf{x}_{1t}\hat{\beta}_1 + \mathbf{x}_{2t}\hat{\beta}_2 + \hat{\mathbf{B}}_N\bar{\boldsymbol{\mu}}\right] \tag{13}$$

$\mathbf{x}_{1t} =$ N by 1 vector of log output levels at time t

$\mathbf{x}_{2t} =$ N by 1 vector of log capital stocks at time t

$\mathbf{G}_N = (\mathbf{I}_N - \rho_1 \mathbf{W}_N)$

$\mathbf{B}_N = (\mathbf{I}_N - \rho_2 \mathbf{M}_N)$

$\bar{\boldsymbol{\mu}} =$ N by 1 vector of estimated time-invariant individual effects

Starting from time *T*, Equation (13) is solved recursively over $t = T + 1, T + 2, \ldots, T + \tau$, using $\mathbf{y}_T$ for $\hat{\mathbf{y}}_T$ to give the first forecast $\hat{\mathbf{y}}_{T+1}$ and then estimates of future $\hat{\mathbf{y}}$ subsequently

Estimating individual effects

For t = 2,...,T

$$\mathbf{y}_t = \gamma \mathbf{y}_{t-1} + \rho_1 \mathbf{W}_N \mathbf{y}_t + \mathbf{x}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{\varepsilon}_t = \mathbf{B}_N \mathbf{u}_t = \mathbf{y}_t - \gamma \mathbf{y}_{t-1} - \rho_1 \mathbf{W}_N \mathbf{y}_t - \mathbf{x}_t \boldsymbol{\beta}$$

SMA errors

$$\mathbf{u}_t = \boldsymbol{\mu} + \mathbf{v}_t = \mathbf{B}_N^{-1}\left[\mathbf{y}_t - \gamma \mathbf{y}_{t-1} - \rho_1 \mathbf{W}_N \mathbf{y}_t - \mathbf{x}_t \boldsymbol{\beta}\right]$$

Error components

$$\boldsymbol{\mu} = \mathbf{B}_N^{-1}\left[\mathbf{G}_N \mathbf{y}_t - \gamma \mathbf{y}_{t-1} - \mathbf{x}_t \boldsymbol{\beta}\right] - \mathbf{v}_t$$

Individual effects

$$\mathbf{v}_t \sim N\left(0, \sigma_\nu^2 \mathbf{I}_N\right)$$

Random draw

outcome is *T*-1 different estimates of $\hat{\boldsymbol{\mu}}$, and so we calculate the across time mean of the $\hat{\boldsymbol{\mu}}$ s to give an estimate of the (*N* x 1) time-invariant vector $\boldsymbol{\mu}$, denoted by $\bar{\boldsymbol{\mu}}$ in equation (13)

Fingleton(2014),Baltagi, Fingleton and Pirotte(2015)

Ex-post prediction

Figure 2: four-step ahead predictions versus observed log employment levels (endogeneity)

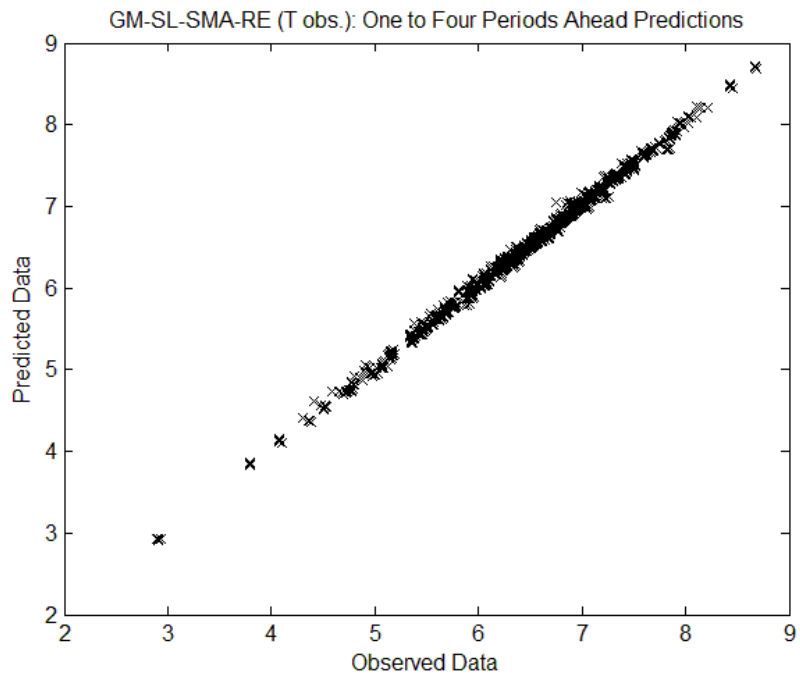


Figure 3 : Observed log employment levels for 2008

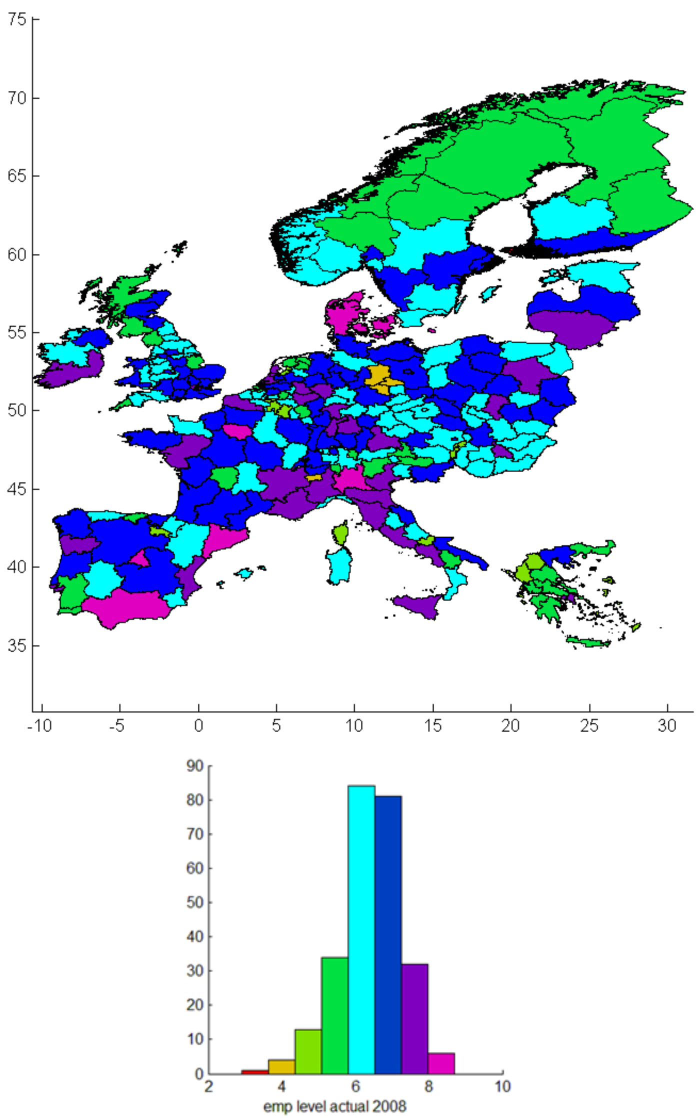
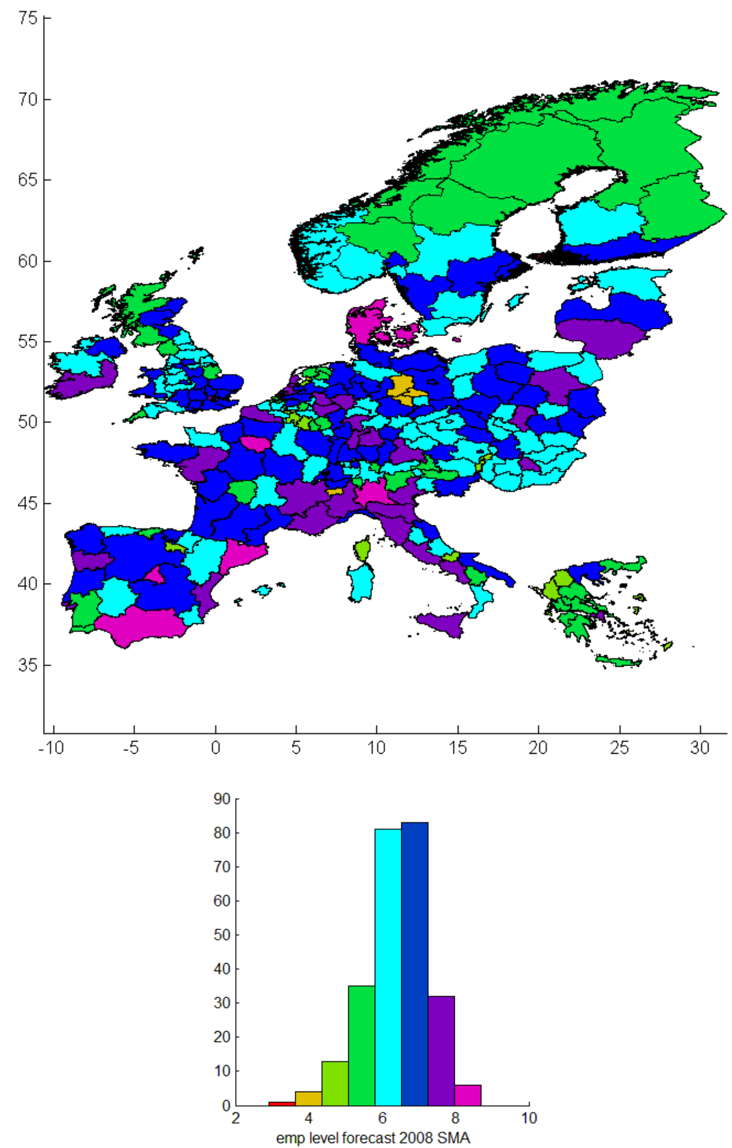


Figure 4: Ex post prediction (endogeneity) of log employment for 2008



Ex-ante prediction

$$\hat{\mathbf{y}}_t = \hat{\mathbf{G}}_N^{-1}\left[\hat{\gamma}\hat{\mathbf{y}}_{t-1} + \tilde{\mathbf{x}}_{1t}\hat{\beta}_1 + \tilde{\mathbf{x}}_{2t}\hat{\beta}_2 + \hat{\mathbf{B}}_N\bar{\boldsymbol{\mu}}\right] \qquad (14)$$

$\tilde{\mathbf{x}}_{1t} =$ assumed levels of log output at time t

$\tilde{\mathbf{x}}_{2t} =$ assumed levels of log capital at time t

Ex ante prediction

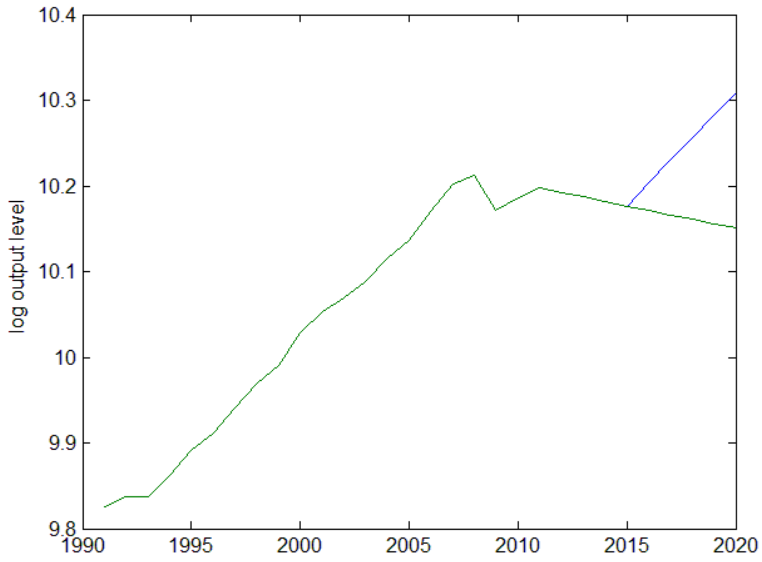
- ‘austerity’ prediction
- what would happen to employment if the growth of output and capital over the period 2012 to 2020 was the same as in the early years of the crisis, that is equal to the EU regions’ means for 2007-2011?
  - -0.5% per annum for output
  - -5% per annum for capital

Ex ante prediction

- ‘boom’ scenario
- what would happen to employment if growth could recover such that the drivers of employment grew at the pre-crisis rate?
    - 1999-2007, 2.7% pa for output, 3% for capital
- growth continues at austerity rates until 2015, then assume that the economy reverts to 1999-2007 growth rates from 2015

Alternative growth scenarios

Figure 5: Paths for log output and capital under austerity and boom scenarios



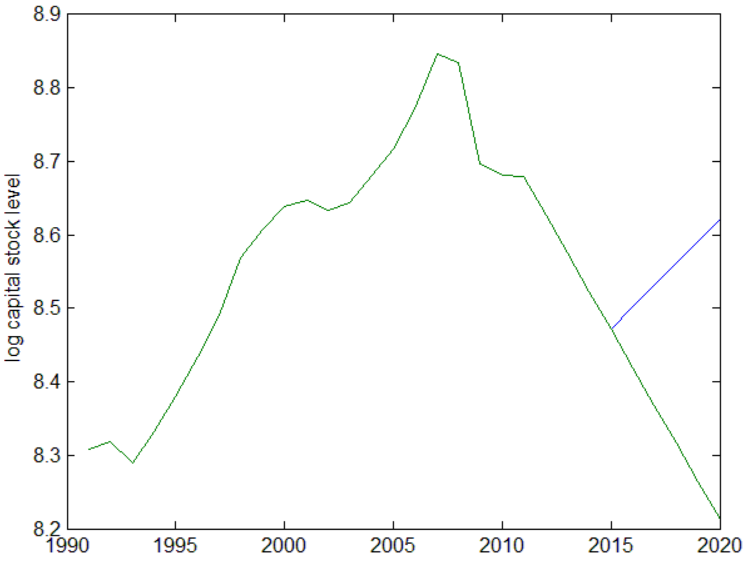


Figure 6: 2020-2007 log employment differences : austerity (assuming endogeneity)

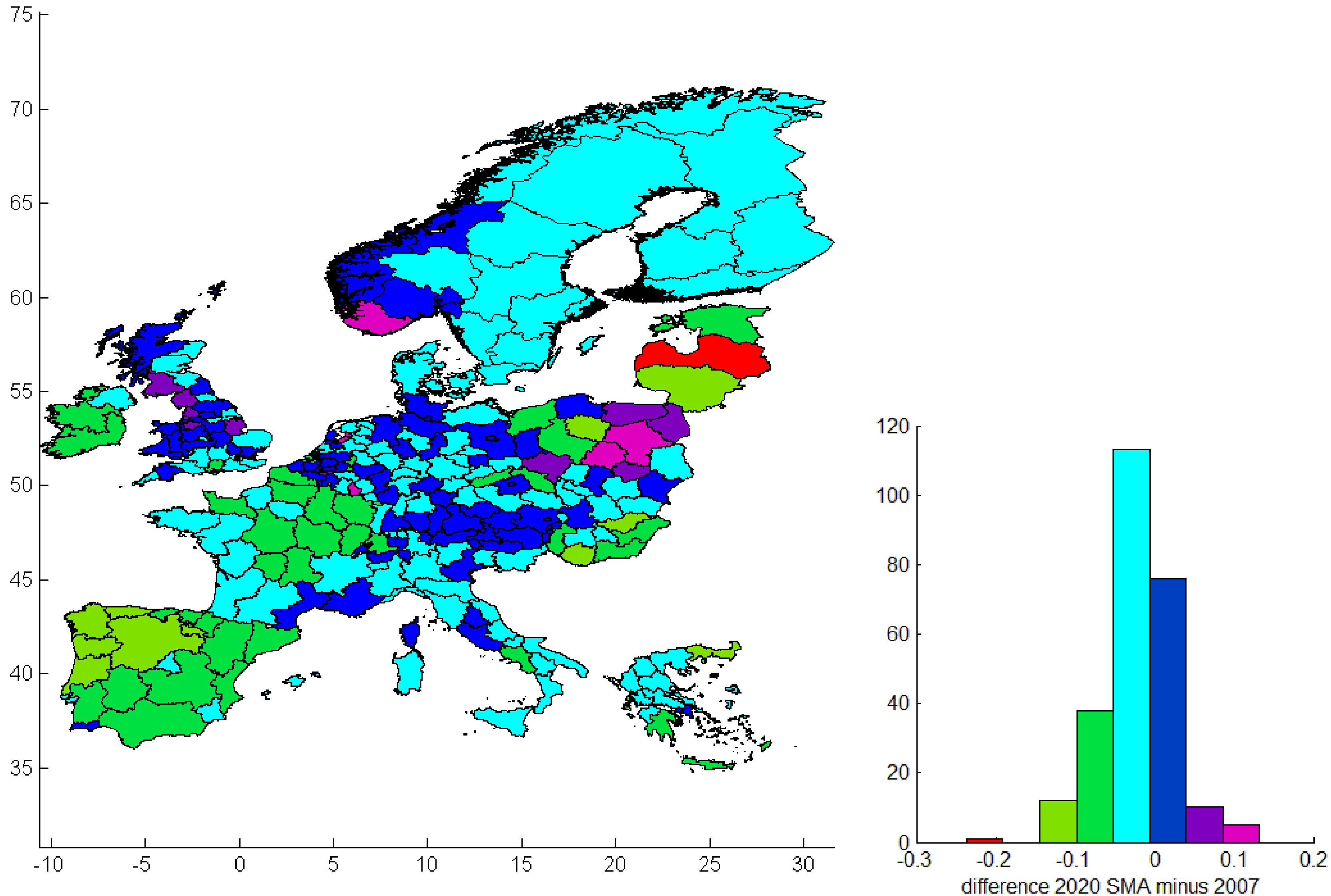
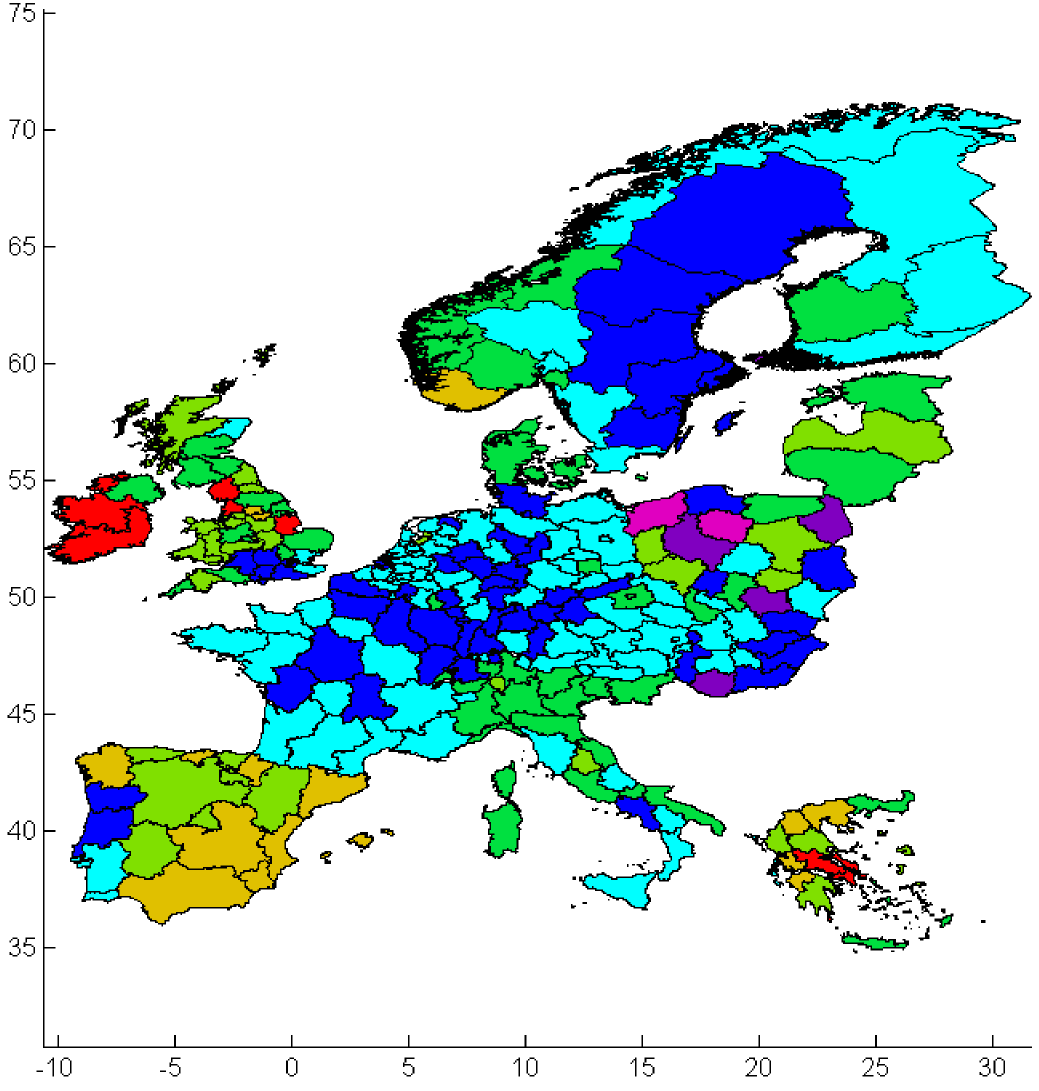
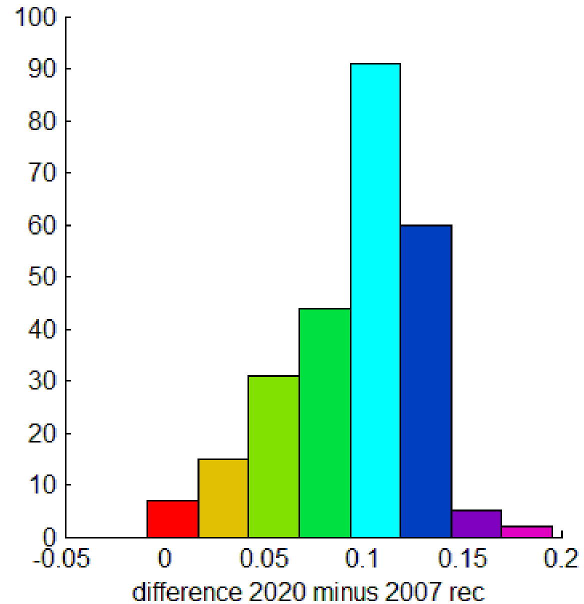


Figure 7: 2020-2007 log employment differences : boom (assuming endogeneity)





commentary

- ‘boom’ would help eliminate the employment crisis in Southern Europe, especially Greece
- BUT a more sustainable, albeit slower, growth rate for the EU as a whole would be a more optimal target for policy makers
  - avoiding the overheating, congestion and inflationary pressures in the core regions of the EU
- BUT slower recovery would probably leave more peripheral regions, especially Greece, at levels of employment below those of 2007

commentary

- UK regional problem ‘writ large’
- contrast between the North and South is a long established feature of the UK economy
- Current political tensions in the UK revolve around the role of austerity
  - For Scotland and the North, austerity is seen as disadvantageous
  - What is needed in many of the older industrial areas are policies that increase demand not reduce it
  - In contrast in the South East especially, excessive growth is accompanied by strong inflationary pressures

commentary

- simulations based on alternative growth scenarios highlight the dilemma that the EU, especially the Eurozone, faces
- Is it possible to impose coordinated centralized policies given the diversity of outcomes, especially between core and periphery?
- Problem : because of connectivity between regions, what happens in one region impacts outcomes in other regions
- So isolated policies tailored to individual regions will only be partially effective

conclusions

- paper has taken a ‘critical’ view of spatial econometrics
- though not too critical because as a practitioner of econometric modelling, I am aware both of the limitations and the benefits

conclusions

- The Achilles heel of spatial econometrics remains the definition and structure of the matrices that govern interaction between regions
- In many examples these problems are swept aside as of no consequence, but it remains true that what is assumed does make a difference
- attempted to come to terms with this by providing a basis for the interaction between regions based on imputed interregional trade flows

conclusions

- ‘spatial econometric models are ad hoc’
- attempted to justify the presence of spatial and temporal spillovers in the model

conclusions

- ‘spatial econometric models are biased because of omitted variables’
- pick up the effects of omitted variables via dynamic spatial panel modelling
- Control for unobservable regional heterogeneity
- Include spatial error process to moderate spatial lag

conclusions

- ‘spatial econometric models do not reveal true causal effects’
- assume that the drivers of employment are endogenous
- Account for spillovers in interpreting impact of changes in output and capital stock via prediction equation

conclusions

- ‘Econometric models are important tools for forecasting and policy analysis, and it is unlikely that they will be discarded in the future. The challenge is to recognise their limitations and to work towards turning them into more reliable and effective tools. There seem to be no viable alternatives’ Pesaran(1990)