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ON THE SIGNIFICANCE OF LABOR REALLOCATION FOR EUROPEAN UNEMPLOYMENT: EVIDENCE FROM A PANEL OF 15 COUNTRIES

On the Significance of Labor Reallocation for European Unemployment: Evidence from a Panel of 15 Countries[*]

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Abstract

We explore the macroeconomic effects of sectoral shifts for a set of 15 European countries. An extensive panel is constructed that allows us to assess the effect of labor reallocation in the European context. Indexes of labor market turbulence based on alternative sectoral disaggregation are constructed. The effect of labor reallocation on unemployment is found to be positive and significant in all different specifications. This remains robust when we consider measures of volatility in the model.

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I.   INTRODUCTION

A disparity of adjustments response across the Euro-area labor markets has characterized the Great Recession and the sovereign debt crises (European Central Bank, 2012). Recently this insight about the relative importance of (within) state regional heterogeneity for unemployment has been explored, with different emphasis on sectoral reallocation or regional mobility using country specific dynamic reduced form equation or panel SVAR's (see Dao et al. (2014), Hogrefe and Sachs (2014) and Beyer and Smets (2015) among others). These approaches have provided contradictory results. Hogrefe and Sachs (2014) have shed doubts on the relevance of sectoral reallocations for some of the "troubled economies" of the EU. On the other hand, Dao et al. (2014) and Beyer and Smets (2015) assign a significant, and possibly increasing, importance to both region-specific shocks and reallocation of jobs (and labor) across regions. In the light of recent advances in dynamic panel data modelling, it is the purpose of this paper to extend these previous results by framing the analysis in a heterogeneous panel data model that allows for cross-sectional dependence.

In this paper we examine the effect of labor reallocation on unemployment for European labor markets within a panel framework that takes into account dynamics, parameter heterogeneity and cross sectional dependence. The contribution of the paper is threefold: (i) we build an extensive dataset of 1165 observations for 15 European countries to assess the significance of labor reallocation on unemployment, (ii) we employ recently developed panel methodologies that allows us to take into account characteristics that are endemic to the hypothesis and (iii) we provide evidence that the sectoral reallocation index remains a significant determinant for rising unemployment even when aggregate volatility and expected volatility measures are taken into account.

The rest of the paper is organized as follows. Section II outlines the background literature on the topic, section III discusses the model and estimation methodology and section IV presents the data. The results are discussed in section V and finally, section VI concludes.

II.   BACKGROUND

Draghi (2014) has recently reminded us that the heterogeneous picture lying behind the aggregate data reflects highly "different initial conditions such as varying sectoral composition of employment". His analysis is consistent with the ECB report on EU labor markets (European Central Bank, 2012) that stresses the structural nature of European unemployment and the limited power of monetary policy in tackling this issue. Structural reforms are indispensable both at the individual state and the Union level. This view has attracted the attention of researchers who have been trying to substantiate it econometrically from different perspectives.

Hogrefe and Sachs (2014) analyse a subset of EU countries (France, Ireland, Italy, Portugal, Spain) and use a difference specification of Okun's approach (Okun, 1962) to estimate separately error correction models for each country. Their findings show that sectoral reallocations drove Spanish unemployment over the decade 2004-2014, while they are not significantly related to unemployment in France, Ireland and Portugal and are only marginally significant in Italy. The paper presents interesting results but focuses on a limited set of countries and the chosen methodology (ADL-reduced form estimation for each country) does not take into account the potential interdependence between countries.

Dao et al. (2014) and Beyer and Smets (2015) are rooted in the pioneering work of Blanchard and Katz (1992) and use panel VAR's. Their focus is on the importance of labor migration for long run labor markets adjustments in both the US and EU. Dao et al. (2014) estimate a system panel VAR with three state level variables: state-relative employment growth, state-relative log employment rate and state-relative log participation rate for Europe and the USA. By imposing suitable restrictions, they conclude that the long-run effect of a state-specific shock on the state employment has decreased over time. Also the short term response of participation rates to labor demand shocks is found to be larger in Europe compared to the US.

Beyer and Smets's (2015) two-steps estimation procedure is aimed first at decomposing regional variables in three orthogonal components (continental, country, regional) via a multi-level factor model and then at estimating the impact of region-specific and country-specific shocks on labor markets via panel VAR's pooled over the relevant subsamples. On

the one hand they highlight the differences between the two sides of the Atlantic: in Europe labor mobility is less important for the adjustment mechanism to region-specific labor demand shocks compared to the US. On the other, they detect convergence of the adjustment process as interstate migration in the US (Europe) is falling (increasing).

As Hogrefe and Sachs (2014), we are interested in testing and measuring the impact of inter-sectoral reallocation on unemployment. However, operationally we are closer to Dao et al. (2014) and Beyer and Smets (2015) though their interest is mainly on migration while ours is on unemployment. Given industrial structures differing across EU states, each state would be affected differently by sectoral shocks. If a shock hits unfavourably the demand composition of a specific state the workers affected will become unemployed, drop out of the labor force or migrate to another country. On the other hand aggregate shocks (e.g. shocks linked to ECB monetary policy) will affect all countries and, even if sectors, and so individual countries, respond differently, it is unlikely they will generate much labor mobility across countries. This holds because the probability of finding a job elsewhere would not be much different.

In this paper we focus on labor reallocation and its impact on the unemployment rate vis-a-vis potentially alternative triggering forces. We capture reallocation via a "purged" Lilien's dispersion proxy (Lilien, 1982). We expand previous work by considering also the impact of volatility measures on unemployment as captured by the so called "uncertainty" indexes which measures the economic policy expected volatility (Bloom (2009)). Caggiano et al. (2014) explore the effects of volatility index (VIX) and economic policy uncertainty index (EPU) shocks on unemployment dynamics using a non-linear VAR for the US. They provide evidence of a significant increase of unemployment after a one standard deviation-shock to volatility and uncertainty proxies. Baker at al. (2015) develop a new index of policy-related economic uncertainty and estimate its dynamic relationship to employment. Their results bear out that the policy uncertainty index leads to a significant decline in employment for the US and for a panel of 12 major economies. Choi and Loungani (2015) similarly, explore the role of uncertainty shocks on unemployment dynamics by distinguishing between aggregate and sectoral channels of volatility and comparing their effects on the unemployment rate. They show that the response of

unemployment to aggregate uncertainty and sectoral uncertainty is different, and thus, that sectoral uncertainty shocks have more persistent effects for unemployment.

In extending the above mentioned literature, we estimate a reduced form panel equation that takes into account dynamics, parameter heterogeneity and cross sectional dependence according to recent advances in the field.[1] Finally, given the recent empirical evidence on the significance of economic volatility and uncertainty shocks for unemployment, we also consider an extended specification accounting for the effect of volatility and expected volatility measures.

III. MODEL AND METHODOLOGY

We estimate an unemployment reduced form equation of the form used by Mills et al. (1995). Lilien's (1982) original approach focused only on monetary shocks vis-à-vis reallocation shocks, while Mills et al. (1995) allow for a larger set of aggregate covariates thus allowing for a more thorough testing of the sectoral shifts hypothesis. Using pooled time-series-cross-section data for the period 1995Q1-2015Q1 and for 15 European countries (N=15 and T=81, results to a total of 1165 observations due to data restrictions and adjustments), we employ a dynamic heterogeneous panel analysis for the equation:

$$U_{i,t} = \mu_i + a_i U_{i,t-1} + \beta_i \sigma^p_{i,t} + \lambda_i' z_{i,t} + u_{i,t} , \qquad (1)$$

where $U_{i,t}$ is unemployment for EU country i at time t; μ_i denotes a set of country-specific fixed effects capturing the influence of unobserved state-specific heterogeneity; $\sigma^p_{i,t}$ is the index of dispersion; the vector $z_{i,t}$ is a vector of EU country specific control variables among which we include the real GDP growth, ΔGDP; the interest rate growth, ΔIR, its (GARCH) variability, H, and the growth rate of government expenditures, ΔG; finally, $u_{i,t}$ is the error term.

The variable $\sigma^p_{i,t}$ is the EU country "purged" measure of employment dispersion across sectors.[2] Letting $N_{j,i,t}$ and $N_{i,t}$ be the employment in sector j in country i at time t for j =

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[1] See Bakas et al. (2013) for a similar approach for the US. See Chudik and Pesaran (2015b) for an extensive survey on heterogeneous panel data models with cross-sectional dependence.

[2] The ten sectors are agriculture, industry, construction, trade, information, financial, real estate, professional, public and other sectors as defined in the OECD Quarterly National Accounts database.

1,2…, *10,* and aggregate employment in country *i* at time *t* respectively, while $N_{j,i,t}/N_{i,t}$ are weights defining by the relative size of each sector in each country, we can measure the "standard" dispersion proxy (Lilien, 1982) for each country *i* at time *t* as follows:

$$\sigma_{it} = \left[\sum_j (N_{j,i,t} / N_{i,t})(\Delta \ln N_{j,i,t} - \Delta \ln N_{i,t})^2 \right]^{1/2} . \quad (2)$$

We filter out any potential aggregate influences from σ_{it} by regressing it on a vector of aggregate variables $\widetilde{w}_{t-k}$:[3]

$$\sigma_{i,t} = \phi_i + \sum_{k=0}^{q} \theta \, \widetilde{w}_{t-k} + \xi_{i,t} . \quad (3)$$

The estimated residual, $\widehat{\xi_{i,t}}$, is then the dispersion measure 'purged' of aggregate effects, denoted hereafter as $\sigma_{i,t}^p$.[4]

We assume a multi-factor error structure so as to take into account cross correlation of the disturbances:

$$u_{i,t} = \gamma'_i f_t + \varepsilon_{i,t}, \quad (4)$$

which we further split (see Chudik et al. (2011) and Chudik and Pesaran (2015b)) as follows:

$$f_t = f^s_t + f^w_t . \quad (5)$$

In Equation (4) f_t is a m-dimensional column vector of unobserved common factors capturing cross-sectional dependencies across countries, the γ'_i are the country specific factor loadings, with $\varepsilon_{i,t} \sim IID$ across *i* and *t*. In Equation (5) $\mathbf{f}^s_t$ and $\mathbf{f}^w_t$ are two vectors of a finite number of 'strong' factors (common global shocks to all EU countries) and of an infinite

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[3] In this case we have used the change of interest rate, its GARCH variability and the growth rate of government consumption expenditure for each country (see also the data section).
[4] The potential sensitivity of Lilien's measure to aggregate shocks was pointed out by Abraham and Katz (1986). The purging methodology is discussed in Gallipoli and Pelloni (2013).

number of 'weak' factors (regional spillover effects across subsets of EU countries) respectively.

We rely on alternative approaches to estimate the impact of labor reallocation on unemployment. Both homogeneous and heterogeneous estimators are used to explore the robustness of the effect. We start with the pooled OLS and the fixed effects (FE) approach which allows the intercepts to differ across countries. Next we move to their extensions proposed by Driscoll and Kraay's (1998) that employ a nonparametric variance-covariance matrix estimation which produces heteroskedasticity and autocorrelation consistent standard errors that remain robust to the presence of generalized forms of spatial and cross-sectional dependence. Furthermore, given the dynamic specification of Equation (1), we proceed and employ the system GMM estimator of Blundell and Bond (1998). To account for the presence of cross sectional dependence in the homogeneous modeling we employ the pooled common correlated effects estimator (CCEP) suggested by Pesaran (2006).

Given the importance of heterogeneity and cross country dependence in the EU context, we proceed to the estimation of heterogeneous panel models with cross-sectional dependence; the heterogeneous version of the CCE estimator (CCEMG) as suggested by Pesaran (2006) and the AMG estimator by Bond and Eberhardt (2009) which allows for parameter heterogeneity and accounts also for cross sectional dependence in the panel. Finally, we implement the recent extension of the Mean Group Common Correlated Effects estimator (dynCCEMG) that is explored in Chudik and Pesaran (2015a) and permits the inclusion of lagged dependent variables and weakly exogenous regressors in the panel data modeling.

IV.   DATA

We employ quarterly data for an unbalanced panel of 15 European Countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom, over the period 1995Q1-2015Q1. Table 1 presents the list of countries and their abbreviations. The data for sectoral employment are from the OECD Quarterly National Accounts while the macroeconomics variables used in the analysis were obtained from OECD's Main Economic Indicators and

Labour Market statistics databases. The reallocation index is computed for each country using the shares of the available sectoral decomposition of quarterly employment based on the following 10 sectors (see note 2). Using this industrial decomposition, we compute measures of reallocation (σ^p) allowing for alternative sectoral disaggregation (4, 5, 8, 9 and 10 sectors respectively).

We use the logarithmic form of the unemployment rate as the dependent variable, $U_{i,t} = ln(un_{i,t})$, where $un_{i,t}$ is the unemployment rate. The macro variables consist of the real GDP, the short term (3 months) interest rate and the general government final consumption expenditure for each country, transformed in first differences, ΔGDP, ΔIR and ΔG respectively.[5] Following Caporale et al. (1996) and Bakas et al. (2013), we proxy the monetary policy variability using the conditional variance (H) derived from a GARCH (1,1) model for the interest rate. Given the literature reviewed in Baker et al. (2015), we explore the addition in the specification of several measures of volatility (expected volatility and stock market volatility) for the EU (and the US).[6,7] Table 2 presents the corresponding summary statistics for all variables used in our analysis. Figures 1 and 2 depict the series of unemployment rate and sectoral reallocation index for the 15 EU countries as well as the EU average. The heterogeneity of the EU labor markets is evident from both Figures.

V.   EMPIRICAL RESULTS

Our analysis starts with the estimation of Equation (1) using an extended dataset of 15 EU countries over the period 1995Q1-2015Q1 (a total of 1165 observations after adjustments). Table 3 presents the estimated coefficients of Equation (1) using alternative pooled estimation techniques: Pooled OLS, (one way and two way) Fixed Effects, system GMM, the Driscoll and Kraay's (1998) Pooled OLS and Fixed Effects estimators which produces robust standard errors to cross-sectional dependence and the Pesaran's (2006)

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[5] We use the short term interest rates obtained by the national Central Banks, while after the introduction of the euro we use the 3-month "European Interbank Offered Rate" from the ECB for the period after each country joined the single currency.

[6] We use the VSTOXX volatility index (VOL^{eu}), obtained from STOXX database, for the EU stock market variability (which is the European equivalent to the VIX index for the US), and the EPU index of Baker et al. (2015) for EU and US (EPU^{eu} and EPU^{us}) respectively. Finally, we use a stock market index ($STOCK^{eu}$) for each country (collected from the OECD database).

[7] Bloom (2013) defines "uncertainty" as forward looking and volatility as realised. Uncertainty can be viewed as 'expected volatility'.

Pooled Common Correlated Effects estimator (without and with state-specific linear trend) that accounts for cross sectional dependence. The coefficient of lagged unemployment is significant and less than unity (greater than 0.9 but lower than 1) capturing the high persistent nature of the European unemployment. The coefficient of labor reallocation as measured by Lilien's proxy (σ^p) is positive and statistically significant across all alternative estimation methods (including the Driscoll and Kraay's (1998) and the Pesaran's (2006) estimators that are robust to cross-sectional dependence and the system GMM approach which is robust to endogeneity issues of the regressors). The values of the σ^p coefficients range from 0.82 (CCEP) to 1.291 (FE$_T$) and are statistically significant in all cases highlighting the importance of labor reallocation for unemployment. These findings reinforce the existing evidence of a significant effect of sectoral shocks (e.g. De Serres et al. (2002) for the EU and Bakas et al. (2013) for the US). The coefficient of the growth rate of GDP is negative and significant and, in a sense, reflects Okun's law. The coefficient of ΔIR is also negative and significant in most of ~~the~~ cases, but with relatively lower significance for unemployment H (the monetary policy GARCH variability) has a small positive and significant coefficient. Finally, the impact of the fiscal policy (ΔG) is found to be negative and significant. Based on the *RMSE* the preferred (homogeneous) model is the pooled CCE (CCEP).

Table 4 presents the heterogeneous slopes estimates that account for cross-sectional dependence (AMG, CCEMG and the dynCCEMG which allows for lagged values of the dependent variable and weakly exogenous regressors in the specification). The coefficient of σ^p remains positive and significant in all cases with values just below unity (ranging from 0.748 (CCEMG$_T$) to 0.880 (CCEMG)). The results based on the heterogeneous estimators (Table 4) highlight the significant effect of the dispersion index on unemployment even when heterogeneity and interdependence among EU states is taken into account. Furthermore, we observe that these heterogeneous estimates (Table 4) are of similar magnitude with the homogeneous estimates of the pooled CCE estimator (columns 7 and 8 of Table 3) where cross country dependence is taken into account. This outcome stresses the importance of controlling for the presence of cross sectional dependence in the European panel context. The results for lagged unemployment confirm the high persistence of EU unemployment. The rest of the coefficients are producing results similar

to the pooled estimates both in significance and sign. The model that minimizes the *RMSE* is the dynCCEMG$_4$ (σ^p coefficient of 0.828).

A. ROBUSTNESS

Our check for robustness is twofold. On the one hand, alternative σ^p indexes are constructed to investigate whether the degree of sectoral disaggregation can affect the results. Table 5 presents the results for labor reallocation that stems from 4, 5, 8, 9 and 10 sectors (the 10 sector σ^p is also employed for the results that were presented in Tables 3 and 4) using the homogeneous DK-FE and the heterogeneous CCEMG estimators. Two issues emerge from the results. First and foremost, we observe that the coefficient of labor reallocation remains positive and significant under all alternative measures of sectoral disaggregation. Second, the magnitude of the σ^p coefficient decreases as the sectoral disaggregation increases.[8] The coefficient of *ΔIR* seems to be more fragile to the alternative measures of reallocation index in the specification as it loses its significance in some cases when employing the CCEMG estimator.

The second route is to consider measures of (expected) volatility and stock market volatility in the empirical specification. Following the contributions of Bloom (2009, 2013) and Baker et al. (2015) we augment the model by considering the effects of volatility. Expected volatility is proxied by the Economic Policy Uncertainty Index (*EPU^{eu}* and *EPU^{us}*) for Europe and the US (see Baker et al. (2015) for an extensive discussion). Alternative measures of volatility include the EU stock market variability index (*VOL^{eu}*) that is measured by the *VSTOXX* volatility index. Finally, we use the stock market index for each country (*STOCK^{eu}*) as a proxy for the stock market activity. The results are presented in Table 6 and Table 7 using the homogeneous DK-FE and the heterogeneous CCEMG estimators respectively. Two significant features emerge from these results. First, looking at Table 6, the measures of expected volatility (*EPU* for Europe and the US) and stock market volatility (*VOL^{eu}*) are affecting in a positive and significant way unemployment (stock market index (*STOCK^{eu}*) has a significant negative sign instead).[9] This finding corroborates Caggiano et al. (2014) and Baker at al. (2015) who provide evidence of a

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[8] As in Bakas et al. (2013) the impact of the dispersion index depends on the level of its disaggregation.

[9] The variables *EPU^{eu}*, *EPU^{us}* and *VOL^{eu}* are common for all EU countries and can be seen as 'observed common factors' in the heterogeneous version of Equation (1) and therefore their coefficients and its significance based on the CCEMG estimator (in Table 7) have to interpreted with caution.

significant positive effect of unemployment to volatility and uncertainty shocks. Second, σ^p remains positive and significant under all different scenarios (with a magnitude comparable to those produced from the specification without the volatility proxies). Choi and Loungani (2015) document the higher importance of sectoral (uncertainty) shocks on unemployment compared to aggregate (uncertainty) shocks for the US. The relative lower estimated coefficients of *EPU* on Table 6 seem to point to the same direction for the EU. Overall the purged dispersion measure remains significant under alternative levels of sectoral disaggregation and when expected volatility and stock market volatility are taken into account.

VI.   CONCLUSIONS

The notion of labor reallocation and its effect on unemployment has generated a strand of literature that focused on the US economy. We revisit the hypothesis by looking at an extensive panel of 15 European countries. The adopted econometric methodology takes into account important characteristics of the hypothesis: dynamics, heterogeneity and cross section dependence. We construct an extensive quarterly panel dataset of 1165 observations. The increased degrees of freedom of the panel framework allow the assessment of the effect of labor reallocation on European unemployment. We employ a battery of alternative pooled and heterogeneous panel estimates. All estimations bear out the positive and statistically significant effect of labor reallocation on unemployment. Robustness includes different labor sectoral disaggregation and the inclusion of alternative volatility measures. These results confirm the economic importance of labor reallocation for the European unemployment.

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TABLES AND FIGURES

PART A: DESCRIPTIVE STATISTICS

Table 1: List of EU Countries and Abbreviations

Country	Abbrev.	Country	Abbrev.
Austria	AT	Italy	IT
Belgium	BE	Luxembourg	LU
Denmark	DK	Netherlands	NL
Finland	FI	Portugal	PT
France	FR	Spain	ES
Germany	DE	Sweden	SE
Greece	GR	United Kingdom	GB
Ireland	IE		
		N = 15, T = 81	

Table 2: Summary Statistics

	Mean	SD	Min	Max
	Sectoral Variables			
Total	11897.883	12040.592	257.450	42774.000
Agriculture	412.583	341.599	4.037	1280.502
Industry	1933.547	2205.590	36.309	8880.000
Construction	841.824	845.009	27.783	3332.000
Trade	2941.812	2938.344	65.965	9884.000
Information	336.318	373.980	8.333	1382.017
Financial	354.348	390.065	29.062	1298.000
Real Estate	120.640	144.112	1.386	503.129
Professional	1359.434	1476.802	28.140	5667.000
Public Sector	2836.501	2908.458	43.822	10278.000
Other Sectors	760.865	873.605	11.068	2992.000
	Macro Variables			
Un. Rate	8.337	4.172	1.867	27.833
U	-2.588	0.449	-3.981	-1.279
σ	0.010	0.007	0.001	0.069
σ^p	0.000	0.007	-0.012	0.060
Real GDP	11.753	1.242	8.648	13.827
Int. Rate	3.091	2.415	-0.113	18.117
GARCH (H)	0.462	0.513	0.000	8.797
Gov. Exp.	10.160	1.323	6.682	12.488
EPU ^{eu}	4.751	0.347	4.100	5.555
EPU ^{us}	4.613	0.303	4.145	5.375
VOL ^{eu}	3.174	0.325	2.569	4.066
STOCK ^{eu}	4.541	0.429	3.247	5.817

Notes: Summary statistics for sectoral employment and Macro series for the full sample, based on *N = 15* and *T = 81*. All variables are defined in the Data section.

PART B: FIGURES

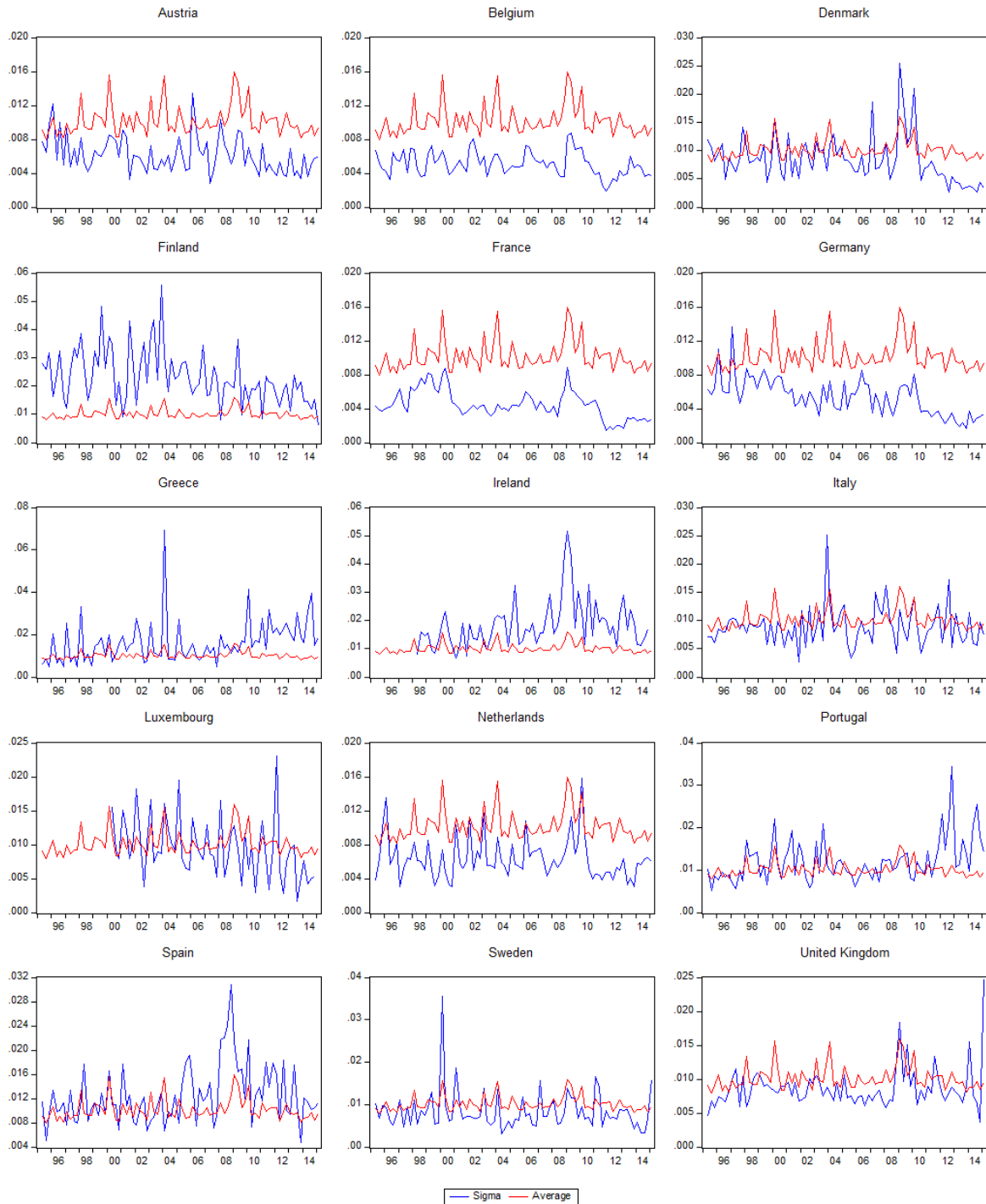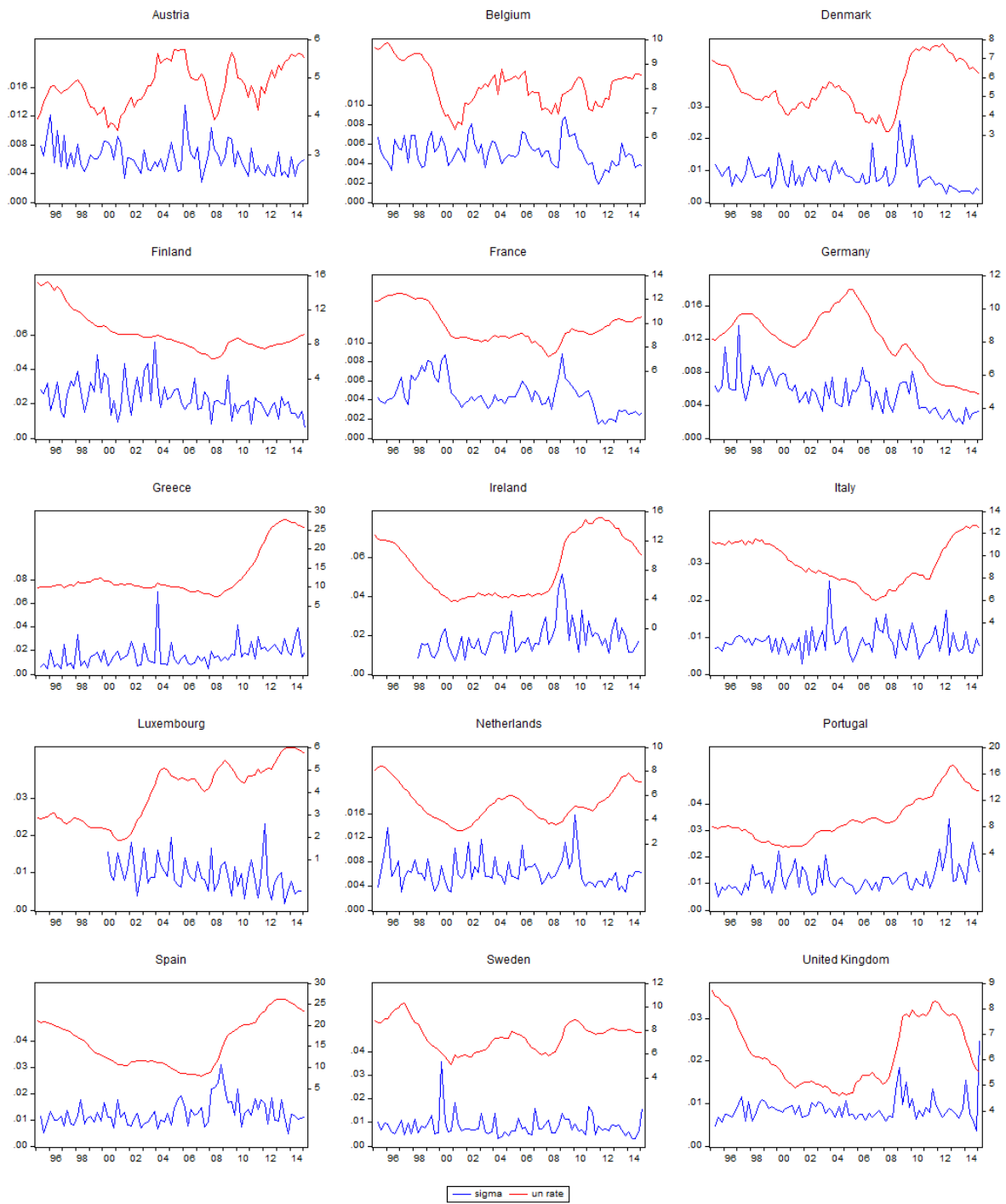Figure 1: Lilien's "Purged" Index for the 15 EU Countries against the EU average

Figure 2: Unemployment Rate and Lilien's "Purged" Index for the 15 EU Countries

PART C: ESTIMATION TABLES

Table 3: Lilien's Index and Sectoral Shifts - Pooled Estimates

	POLS	FE	FE$_T$	GMM	DK-POLS	DK-FE	CCEP	CCEP$_T$
U_{Lagged}	0.984**	0.973**	0.975**	0.978**	0.984**	0.973**	0.966**	0.965**
	(292.51)	(161.34)	(136.64)	(88.81)	(181.71)	(105.34)	(135.35)	(129.57)
σ^p	0.905**	1.277**	1.291**	0.976**	0.905**	1.277**	0.820**	0.827**
	(4.32)	(2.65)	(2.71)	(2.23)	(2.59)	(2.61)	(3.44)	(3.33)
ΔGDP	-1.020**	-1.027**	-0.599**	-1.090**	-1.020**	-1.027**	-0.345**	-0.337**
	(-7.64)	(-4.18)	(-3.57)	(-4.47)	(-5.58)	(-6.01)	(-2.37)	(-2.23)
ΔIR	-0.018**	-0.018**	-0.003	-0.021**	-0.018**	-0.018**	-0.004	-0.004
	(-4.04)	(-2.54)	(-0.54)	(-3.22)	(-2.79)	(-2.90)	(-1.24)	(-1.20)
H	0.011**	0.010**	0.012**	0.011**	0.011**	0.010**	0.012**	0.012**
	(4.35)	(4.58)	(5.76)	(3.40)	(2.89)	(2.46)	(4.73)	(4.51)
ΔG	-0.230**	-0.287*	-0.269*	-0.299*	-0.230**	-0.287**	-0.220**	-0.217**
	(-2.90)	(-1.98)	(-2.13)	(-1.70)	(-3.14)	(-4.40)	(-2.76)	(-2.62)
Obs	1165	1165	1165	1165	1165	1165	1165	1165
N	15	15	15	15	15	15	15	15
T	78	78	78	78	78	78	78	78
RMSE	0.0396	0.0389	0.0359	0.0397	0.0396	0.0399	0.0324	0.0335
Hansen-J				1.00				
AR(1)				0.00				
AR(2)				0.40				

Notes: FE and FE$_T$ – one way and two way Fixed Effects estimator respectively. DK POLS and DK FE –Driscoll and Kraay's (1998) Pooled OLS and Fixed Effects estimators. GMM – Blundell and Bond (1998) System GMM estimator. CCE and CCE$_T$ – the Pesaran (2006) pooled common correlated effects estimator (without and with state-specific linear trend). t-statistics in parentheses. All estimations were carried out using robust standard errors. RMSE refers to the root mean squared error. Hansen J refers to the p-value of the Hansen test for the validity of over-identifying restrictions. AR (1) and AR (2) refer to the p-value of the test for first-order and second-order residual serial correlation. * and ** denotes significance at the 10% and 5% significance levels, respectively.

Table 4: Lilien's Index and Sectoral Shifts – Heterogeneous Estimates

	AMG	CCEMG	CCEMG$_T$	dynCCEMG$_1$	dynCCEMG$_4$
U_{Lagged}	0.939**	0.942**	0.944**	0.944**	0.917**
	(62.78)	(53.43)	(52.98)	(56.28)	(42.12)
σ^p	0.831**	0.880**	0.748**	0.856**	0.828*
	(2.27)	(3.08)	(2.61)	(2.61)	(1.72)
ΔGDP	-0.986**	-0.585**	-0.601**	-0.461**	-0.506*
	(-3.22)	(-3.08)	(-2.51)	(-2.27)	(-1.81)
ΔIR	-0.022**	-0.043	-0.045	-0.002	-0.008
	(-5.32)	(-1.52)	(-1.56)	(-0.28)	(-1.32)
H	0.010**	0.046*	0.052*	0.004	0.005
	(2.17)	(1.75)	(1.93)	(0.71)	(1.05)
ΔG	-0.089	-0.218**	-0.184*	-0.179*	-0.278**
	(-0.68)	(-2.37)	(-1.89)	(-1.80)	(-2.04)
Obs	1165	1165	1165	1152	1113
N	15	15	15	15	15
T	78	78	78	77	74
RMSE	0.0342	0.0285	0.0282	0.0279	0.0229

Notes: AMG – Bond and Eberhardt's (2009) Augmented Mean Group estimator. CCEMG and CCEMG$_T$ – Pesaran's (2006) Common Correlated Effects Mean Group estimator (without and with state-specific linear trend). dynCCEMG$_1$ and dynCCEMG$_4$ – Chudik and Pesaran's (2015a) Dynamic Common Correlated Effects Mean Group estimator (augmented with one and four additional lags of the cross-section averages). t-statistics in parentheses. RMSE refers to the root mean squared error. * and ** denotes significance at the 10% and 5% significance levels, respectively.

Table 5: Lilien's Index and Sectoral Shifts – Alternative Sectoral Decomposition

	DK-FE	CCEMG	DK-FE	CCEMG	DK-FE	CCEMG	DK-FE	CCEMG	DK-FE	CCEMG
U_{Lagged}	0.973**	0.943**	0.974**	0.943**	0.973**	0.941**	0.973**	0.941**	0.973**	0.942**
	(105.76)	(56.26)	(108.87)	(57.34)	(105.03)	(51.96)	(106.33)	(53.33)	(105.34)	(53.43)
σ_4^p	2.097**	1.207**								
	(3.29)	(3.62)								
σ_5^p			2.243**	1.158**						
			(3.88)	(3.32)						
σ_8^p					1.199**	0.981**				
					(2.29)	(2.67)				
σ_9^p							1.394**	1.030**		
							(2.74)	(3.24)		
σ_{10}^p									1.277**	0.880**
									(2.61)	(3.08)
ΔGDP	-1.070**	-0.647**	-1.060**	-0.629**	-1.073**	-0.656**	-1.067**	-0.650**	-1.027**	-0.585**
	(-6.24)	(-3.32)	(-6.49)	(-3.27)	(-5.92)	(-3.50)	(-6.07)	(-3.45)	(-6.01)	(-3.08)
ΔIR	-0.018**	-0.039*	-0.018**	-0.039*	-0.018**	-0.042	-0.018**	-0.041	-0.018**	-0.043
	(-2.87)	(-1.72)	(-2.95)	(-1.71)	(-2.83)	(-1.54)	(-2.87)	(-1.56)	(-2.90)	(-1.52)
H	0.010**	0.045*	0.010**	0.045*	0.010**	0.047*	0.010**	0.047*	0.010**	0.046*
	(2.57)	(1.73)	(2.85)	(1.76)	(2.34)	(1.71)	(2.52)	(1.71)	(2.46)	(1.75)
ΔG	-0.276**	-0.189**	-0.274**	-0.186**	-0.290**	-0.214**	-0.285**	-0.208**	-0.287**	-0.218**
	(-4.14)	(-2.02)	(-4.15)	(-1.99)	(-4.39)	(-2.37)	(-4.33)	(-2.27)	(-4.40)	(-2.37)
Obs	1165	1165	1165	1165	1165	1165	1165	1165	1165	1165
N	15	15	15	15	15	15	15	15	15	15
T	78	78	78	78	78	78	78	78	78	78
$RMSE$	0.0395	0.0283	0.0392	0.0283	0.0400	0.0285	0.0399	0.0285	0.0399	0.0285

*Notes: DK FE denotes the Driscoll and Kraay's (1998) Fixed Effects estimator and the CCEMG denotes the Pesaran's (2006) Common Correlated Effects Mean Group estimator. t-statistics in parentheses. RMSE refers to the root mean squared error. * and ** denotes significance at the 10% and 5% significance levels, respectively.*

Table 6: Lilien's Index and Sectoral Shifts – Impact of Volatility (DK-FE)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
U_{Lagged}	0.970**	0.977**	0.984**	0.966**	0.974**	0.968**	0.974**	0.978**	0.965**	0.969**
	(100.78)	(101.96)	(108.69)	(92.77)	(118.46)	(114.59)	(115.21)	(113.89)	(103.19)	(108.39)
σ^p	1.280**	1.164**	1.192**	1.115**	1.356**	1.450**	1.306**	1.212**	1.233**	1.422**
	(2.66)	(2.30)	(2.17)	(2.24)	(2.77)	(3.09)	(2.68)	(2.45)	(2.48)	(2.94)
EPU^{eu}	0.024**				0.019*	0.024**				0.022**
	(3.78)				(1.86)	(4.30)				(2.69)
EPU^{us}		0.034**					0.028**			
		(3.87)					(4.63)			
VOL^{eu}			0.031**		0.021**			0.015**		0.003
			(4.68)		(2.20)			(2.36)		(0.43)
$STOCK^{eu}$				-0.026**					-0.020**	
				(-5.30)					(-3.75)	
ΔGDP	-1.060**	-0.964**	-1.096**	-1.203**	-1.003**	-0.875**	-0.818**	-0.852**	-1.019**	-0.788**
	(-3.92)	(-4.62)	(-5.43)	(-5.10)	(-4.49)	(-4.98)	(-5.22)	(-5.05)	(-5.84)	(-4.58)
ΔIR						-0.014**	-0.015**	-0.026**	-0.014**	-0.022**
						(-2.66)	(-2.80)	(-4.25)	(-2.38)	(-4.21)
H						0.014**	0.011**	0.006	0.009**	0.013**
						(3.52)	(3.14)	(0.83)	(2.30)	(2.12)
ΔG						-0.227**	-0.222**	-0.285**	-0.277**	-0.235**
						(-3.99)	(-4.10)	(-4.56)	(-4.40)	(-4.44)
Obs	1165	1165	967	1165	967	1165	1165	967	1165	967
N	15	15	15	15	15	15	15	15	15	15
T	78	78	65	78	65	78	78	65	78	65
$RMSE$	0.0410	0.0403	0.0418	0.0413	0.0418	0.0395	0.0391	0.0407	0.0400	0.0407

Notes: DK FE denotes the Driscoll and Kraay's (1998) Fixed Effects estimator. t-statistics in parentheses. RMSE refers to the root mean squared error. * and ** denotes significance at the 10% and 5% significance levels, respectively.

Table 7: Lilien's Index and Sectoral Shifts – Impact of Volatility (CCEMG)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
U_{Lagged}	0.959**	0.947**	0.941**	0.952**	0.942**	0.940**	0.926**	0.922**	0.936**	0.923**
	(57.89)	(48.14)	(37.91)	(48.77)	(38.64)	(43.88)	(40.14)	(33.43)	(46.95)	(32.21)
σ^p	0.668*	0.660*	1.070**	0.570	1.067*	0.707**	0.754**	1.301**	0.634**	1.372**
	(1.87)	(1.88)	(2.10)	(1.63)	(1.94)	(2.36)	(2.59)	(2.31)	(2.41)	(2.43)
EPU^{eu}	0.003				0.004	-0.001				0.001
	(0.33)				(0.52)	(-0.14)				(0.07)
EPU^{us}		-0.004					-0.008			
		(-0.46)					(-0.97)			
VOL^{eu}			-0.004		-0.006			-0.005		-0.005
			(-0.47)		(-0.81)			(-0.50)		(-0.61)
$STOCK^{eu}$				-0.024					-0.030*	
				(-1.41)					(-1.71)	
ΔGDP	-0.747**	-0.653**	-0.795**	-0.707**	-0.810**	-0.594**	-0.509**	-0.619**	-0.612**	-0.663**
	(-3.67)	(-3.19)	(-2.93)	(-2.89)	(-2.95)	(-3.24)	(-2.86)	(-2.24)	(-2.35)	(-2.37)
ΔIR						-0.042	-0.043	-0.025	-0.048	-0.024
						(-1.49)	(-1.48)	(-0.64)	(-1.46)	(-0.62)
H						0.043*	0.046*	0.082**	0.041**	0.088**
						(1.79)	(1.72)	(3.07)	(2.14)	(3.13)
ΔG						-0.183**	-0.219**	-0.147	-0.186**	-0.144
						(-2.09)	(-2.62)	(-1.35)	(-2.05)	(-1.38)
Obs	1165	1165	967	1165	967	1165	1165	967	1165	967
N	15	15	15	15	15	15	15	15	15	15
T	78	78	64	78	64	78	78	64	78	64
RMSE	0.0305	0.0305	0.0313	0.0301	0.0308	0.0278	0.0278	0.0280	0.0274	0.0275

Notes: CCEMG denotes the Pesaran's (2006) Common Correlated Effects Mean Group estimator. t-statistics in parentheses. RMSE refers to the root mean squared error. * and ** denotes significance at the 10% and 5% significance levels, respectively.