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Employment Resilience in Europe and the 2008 Economic Crisis: Insights from Micro Level Data

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Abstract

This paper analyses employment resilience to the 2008 economic crisis using individual level data from the European Social Survey (ESS) combined with NUTS1 regional economic statistics. It models employment outcomes for individuals for 2002 to 2008 and generates counterfactual outcomes for 2010 for individual-level employment assuming there is no recession. A resilience index, based on the difference between employment outcomes assuming actual economic conditions and a no-recession counterfactual, is generated. Resilience varies substantially and is higher in German and French regions than in peripheral regions. Highly educated individuals, middle-aged individuals, unionised workers and males are more resilient.

Key Words: Regional Resilience, European Regions, Employment Resilience

JEL: R11, J21, O18

1. Introduction

Recently there has been considerable attention paid to the impact of shocks to both regional and national economies. These studies typically focus on cities, regions or nations as the unit of analysis (FINGLETON and PALOMBI, 2013; FINGLETON et al., 2015; HILL et al., 2008; MARTIN, 2012; ORMEROD, 2010) and use a variety of different approaches such as case studies, indices, time series models and structural economic models (MARTIN and SUNLEY, 2013). However, to date there has been relatively little analysis of resilience in the regional context which uses the individual as the unit of analysis. This paper provides insights into how individual specific characteristics and regional variations can help explain the resilience of employment outcomes during an economic crisis. The paper focuses on the crisis as it was experienced in 2010, following crisis impacts going forward from 2008.

Using data from the European Social Survey (ESS), a model of employment outcomes for individuals over the period 2002 to 2008 is estimated. Data are available for this period from four waves of the ESS carried out in 2002, 2004, 2006 and 2008. The model explains individual-level employment outcomes using individual specific variables together with a regional economic variable (namely unemployment rates in the NUTS1[i] region in which the individual is located). The estimated model parameters allow for the generation of predicted outcomes for individuals in 2010 which are based on the economic conditions prevalent across NUTS1 regions at this point in the recession cycle. These are compared to the predictions based on the levels of explanatory variables as they would have been had the 2008 recession not occurred. These predictions are referred to as the no-recession counterfactual. Given these two sets of predictions, one based on realised values of the explanatory variables over the period from 2008 and the other a no-recession counterfactual set of predictions, measures of employment resilience are generated based on the difference between the predictions. This allows for an evaluation of the effect on resilience of individual characteristics such as education and age, and the effect of regional unemployment rates.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of the concept of regional resilience. Section 3 provides a review of studies which have considered the drivers, both individual and regional, of employment outcomes. Section 4 outlines our modelling approach and discusses the generation of our counterfactual employment outcomes and resilience index. Section 5 describes the data used in this analysis and Section 6 presents our model estimates. Section 7 considers the impact of individual characteristics on the resilience of employment outcomes. Finally, Section 8 concludes.

2. Regional Resilience

The concept of regional resilience has received increasing attention since the 2008 economic crisis (FINGLETON and PALOMBI, 2013; MARTIN, 2012; MARTIN and SUNLEY, 2013; SIMMIE and MARTIN, 2010) but resilience per se can be related to economic models developed by FRIEDMAN (1964, 1993) and has an earlier provenance going back to the concept of hysteresis, as discussed for example in ROMER (2001). This paper specifically focuses on the resilience of employment to economic shocks. At an aggregate regional level BLANCHARD and SUMMERS (1987) (in the context of unemployment) note that the concept of hysteresis can refer to 'the development of alternative theories of unemployment embodying the idea that the equilibrium unemployment rate depends on the history of the actual unemployment rate. Such theories may be labelled hysteresis theories after the term in the physical sciences referring to situations where equilibrium is path-dependent' (pp 290). Thus a negative shock leading to permanently higher unemployment may occur if the long term unemployed lose skills and miss out on job training, so that they ultimately become unemployable. In contrast, the employed continue to benefit from learning-by-doing. This viewpoint of hysteresis in unemployment is supported by JAEGER AND PARKINSON (1994) and JACOBSON, VREDIN and WARNE (1997).

In a European regional context there has been much discussion as to the negative impact of economic shocks from 2008 on employment. For example FINGLETON et al. (2012) analyse the response of employment in UK regions to the crisis and suggest that output shocks can have a persistent negative effect on employment. CELLINI and TORRISI (2014), using a similar approach, note that regional resilience in output can vary dramatically across regions and can help explain long run differences in the growth paths of regional economies. FINGLETON et al. (2015), using a dynamic spatial panel model analyse the impact of shocks on the Eurozone, concluding that there was substantial heterogeneity in the responses of regional economies to the 2008 economic crisis. DAVIES (2011) provides an analysis of the resilience of employment to economic shocks using EU regional data and the impact that policy can play in stimulating resilience. BAILEY and BERKELEY (2014) provide an analysis of the impact of the 2008 economic crisis on the West Midlands region of the UK and contextualises the response of this region to the crisis using MARTIN's (2012) four dimensions of resilience. At a national level, DORAN and FINGLETON (2014) find that output shocks have a negative effect on employment[ii] that is persistent.

A number of alternative methodologies have been employed in the analysis of resilience. Appendix 1 provides a typology of these resilience studies, based upon, and extending, the typology presented in MARTIN and SUNLEY (2014). These alternative methods are briefly defined as follows. The case study approach is essentially descriptive in nature and focuses on one or a small number of regions. Typically a regional specific shock is studied such as the decline of a particular industry (BAILEY and BERKELEY, 2014). When more regions are considered a common approach is the construction of resilience indices. These provide insight into the severity of shocks as well as the extent of recovery. They are based around the identification of a particular time period when a shock occurs and are sensitive to the exact specification of this period (MARTIN, 2012), and usually capture the extent of decline followed by the speed of recovery. Time series analysis, often in the form of vector autoregressive or vector error correction models, is typically employed for regional resilience studies which focus on a relatively small number of regions but over a long time period (usually utilising quarterly data). An advantage of these models is their statistical robustness, however, they are limited to small numbers of regions (or else the methodology becomes unwieldy) and also necessitate a long time period for analysis (FINGLETON et al., 2012). Fourthly, an analysis based on formal economic models utilising spatial panel econometric techniques can be utilised. The types of regional economic models utilised vary from those based on the Wage Curve (FINGLETON and PALOMBI, 2013) to the wide family of models whose provenance is the Dixit-Stiglitz theory of imperfect competition (DORAN and FINGLETON, 2013). The final type of analysis is relatively new and is based on merging individual level data with regional data to analyse the impact of economic shocks on individuals (DORAN and FINGLETON, 2015). The approach adopted by this paper is to use the final typology, of merging individual and regional data, by building on the DORAN and FINGLETON (2015) methodology to analyse employment outcomes. Analysis at the individual level is still relatively rare but it advantageously allows one to capture effects which might otherwise be difficult to model, and the necessary individual level data are increasingly accessible. Also, increasingly, techniques to exploit such data are being developed and becoming more readily available. The present paper is set in the context of these recent developments.

To summarise, the paper analyses the resilience of employment to economic shocks, not at an aggregate regional level, but at the level of the individual. It focuses on the response of individuals to the 2008 economic crisis, controlling for individual specific factors such as age, education etc. while also incorporating regional (NUTS 1 level) economic indicators which may also affect individual employment probabilities.

3. Determinants of Employment

The model specification adopted in this paper is based on the extensive literature which considers the determinants of (un)employment outcomes, both at the level of individuals and of regions. At the individual level, prominent among factors which have been found to be important are age, education, gender and family composition (BAUM and MITCHELL, 2008). Thus individuals with higher levels of educational attainment are more likely to be employed than those with lower levels while those from a disadvantaged background are less likely to be employed. Ethnicity and whether or not a person is an immigrant are also evidently factors affecting employment outcomes (WANG and LYSENKO, 2014), but some other factors, such as gender, are more ambiguous with mixed results coming from the literature (BAUM and MITCHELL, 2010).

In line with the approach adopted in this paper, recently there has been a suggestion in the literature of the importance of controlling for regional factors when considering individual's employment outcomes. BAUM and MITCHELL (2010) note that employment outcomes have typically been analysed either using micro data to assess the importance of individual level characteristics on the likelihood of employment/unemployment, or at an aggregate regional level focussing on regional employment levels. However, they suggest that it is the combination of both individual and regional level data which could be the most informative and that a two-level approach which considers both elements is needed[iii]. Their approach is to model individual employment outcomes as a function of educational attainment, age and other socio-demographic factors as well as regional employment conditions such as the proportion of people who are employed. Further application of this mixed-level approach is given in BAUM et al. (2008), BAUM and MITCHELL (2008, 2011) and in WANG and LYSENKO (2014) who, in a different context, also note that an individual's employment outcome is dependent upon his or her individual skills and experience but also upon the characteristics of the labour market within which the individual is embedded. They note that factors such as economic structure and average educational attainment of the labour force (as well as individual characteristics) impact upon individual's performance.

4. Empirical Model

4.1 Modelling Individual Employment Outcomes

The starting point of this paper is a model of the probability of employment as set out in equation (1):

$$E_{it} = F\left[\alpha_0 + X_{it}\beta + \lambda U_{rt} + \rho W_r U_t + \mu_r + \mu_t\right]; \forall r, i, t \tag{1}$$

In which E_{it} is the probability of employment for individual *i* at time period *t* and *F* denotes the cumulative normal distribution function which maps the linear predictor into the 0/1 space. The constant term is denoted by α_0, and U_{rt} is the unemployment rate in region *r* in time period *t* and λ is the associated coefficient. At the individual level X_{it} denotes individual specific characteristics including, among other factors, the age, gender and educational attainment of individual *i* at time *t*, and β is the associated vector of coefficients. The term $W_r U_t$ denotes the weighted average of unemployment rates 'near' to region *r*, with the associated coefficient ρ. This controls for potential spillovers in labour market effects across regions. W_r is the *r*'th row of the spatial weights matrix *W* which is an n by n contiguity matrix, where n is the number of regions, so that cells are allotted the value 1 when a (row and column) pair of regions share a border and zero otherwise. This is subsequently row standardised so that rows of W sum to 1. The 1 by n row vector W_r is then post-multiplied by n by 1 vector U_t yielding a spatial lag of U_{rt}, $\forall r,t$. This paper also accounts for unobservable time-invariant factors via the regional specific fixed effects μ_r, and unobservable factors through time via the year-specific fixed effects μ_t. Estimation is by maximum likelihood, but we also invoke instrumental variable Probit as mentioned subsequently.

The four waves of the European Social Survey question different individuals in each wave, and so is not a true panel data set-up, but rather a pseudo panel. This means that it is not possible to include individual fixed effects in the model, which would control for time-invariant individual unobservable heterogeneity[iv], as the same individuals are not observed over time. A similar situation is faced by DALMAZZO and DE BLASIO (2007a, b), DI ADDARIO and PATACCHINI (2008) and BRATTI and LEOMBRUNI (2009) who also use pseudo-panels. However it is possible to capture unobservable effects at the regional level via the presence of fixed NUTS1-level effects (denoted by μ_r) and fixed effects for each time period through the inclusion of μ_t. Region and time fixed effects control for differences in the expected employment outcomes of individuals across regions and time which are not captured by our other independent variables. Accordingly, the estimation of equation (1) containing individual and regional level variables, together with the regional fixed effects, implies, as is standard in the panel data literature (RAUCH, 1993; WOOLDRIDGE, 2002) that there are no omitted (time-invariant) variables at the regional level which could induce omitted variable bias.

Another issue, as demonstrated by MOULTON (1990), regarding the inclusion of micro level data with aggregated regional level data, is that there are potential implications for the standard errors of our estimated model. MOULTON (1990) notes that even the slightest level of (positive) correlation within groups in the error term can cause serious downward bias in the estimated standard errors and therefore upward bias in t ratios leading to Type I error occurring at a rate higher than the nominal 5%. This is also noted in recent work by CANTON (2009) and BAUM and MITCHELL (2010). They point out that it is likely that observations will be correlated within regions as region specific elements may be impacting on all the people within that region. Therefore, since (positive) intra-region correlation within the regression model is expected, the standard modification for intra-group dependence which produces larger than otherwise standard errors (and adjusts the variance-covariance matrix), and avoids upwardly biased t-ratios, is used. The final estimation procedure for equation (1) is a probit model where the error terms are clustered.

An additional consideration is the potential for bias due to endogeneity. As it turns out, this is evidently not an issue, as the Wald test does not reject the null hypothesis of exogeneity (STATA, 2009). However generally in this kind of analysis there is reason to suspect that endogeneity bias might be present, as discussed in Appendix 2, and therefore as a precaution some ancillary estimates based on the methodology outlined in the Appendix using an instrumental variable probit model are presented[v]. However the outcomes (Table 3) are very similar to the standard probit model, which is used as the basis for projecting the counterfactual series, as our Wald test suggests that it is legitimate to treat the unemployment rate as exogenous.

4.2 Generating a Counterfactual Employment Outcome

Normally, as in DORAN and FINGLETON (2014) who consider deviations in actual GDP from a counterfactual of GDP, the observed outcome in the post-estimation period would be compared with what is predicted under the counterfactual. In the current modelling set-up however, there is a binary response variable and no observed post-estimation employment outcomes, and to work around this shortfall the paper simply uses predicted employment probabilities under two scenarios, one is that the economic shock did not occur (the counterfactual), and the other is that it did occur. Therefore, the analysis is based on differences at the individual level between the probability of employment estimated under the economic conditions that actually prevailed and under counterfactual economic conditions. This enables an assessment of the impact of individual-level and region-level factors on resilience to the crisis as it unfolded over the period 2008-2010.

The starting point therefore is to generate the predicted probability of an individual being in employment based on the individual's characteristics and on the observed, actual, unemployment rate in, and contiguous to, the individual's region of employment. This is given as:

$$\hat{E}_{i2010} = F\left[\hat{\alpha}_0 + X_{i2010}\hat{\beta} + \hat{\lambda}U_{r2010} + \hat{\rho}W_r U_{2010} + \hat{\mu}_r + \hat{\mu}_{2006}\right]; \forall i, r \tag{2}$$

Where $\hat{\bullet}$ indicates an estimated value. The coefficient estimates are those obtained from equation (1) using data from 2002, 2004, 2006 and 2008. Unobservable time-invariant factors are accounted for via the estimated regional specific fixed effects $\hat{\boldsymbol{\mu}}_{\boldsymbol{r}}$, and temporal variation is controlled for by the presence of the year-specific fixed effect for (arbitrarily) 2006 denoted by $\hat{\mu}_{2006}$. Since the aim is to estimate the employment probability of each individual $\hat{E}_{i2010}; \forall i$, , under recession conditions, equation (2) uses the actual 2010 values of the regional unemployment variable $U_{r2010}; \forall r$.

The predicted probabilities under the no recession counterfactual are given by equation (3)

$$\bar{E}_{i2010} = F\left[\hat{\alpha}_0 + X_{i2010}\hat{\beta} + \hat{\lambda}\bar{U}_{r2010} + \hat{\rho}W_r\bar{U}_{2010} + \hat{\mu}_r + \hat{\mu}_{2006}\right] \tag{3}$$

in which all the values are identical to equation (2) except for $\bar{U}_{r2010}$ which is the counterfactual unemployment rate for region r had the 2008 economic crisis not occurred, and $\bar{U}_{2010}$ is the corresponding n by 1 vector. The mechanisms used to obtain the counterfactual input series are described in Section 4.3. The predicted probability $\hat{E}_{i2010}$ differs from $\bar{E}_{i2010}$, since these probabilities corresponding respectively to the actual observed economic conditions in the NUTS region in which individual i is employed and the economic conditions under the counterfactual which assumes that the economic crisis did not occur.

In equations (2) and (3), the individual specific factors, given as X_{i2010}, are simply the observed 2010 indicators for education, gender etc. Observed rather than simulated indictors are employed because, as argued below, it is not expected these variables will have been affected by the economic crisis. Therefore, the sole driver of the difference between equation (2) and (3) is the regional indicator which changes according to the assumptions made about the economic crisis.

The assumption that the individual level variables are not affected by the recession is a theoretical one. While variables such as gender and age will not have been impacted by the recession others such as education or union membership might have been. It is assumed that given the onset of the crisis in 2008, by 2010 an individual will not have had sufficient time to have dramatically changed his/her educational attainment. Therefore, while the crisis may have forced some unemployed individuals back into education, in the two year period considered by this paper is not likely to have had a major impact. For instance it is unlikely in the two year period an individual will have moved from post-secondary education to having completed tertiary education. Union membership is somewhat more problematic as people can quickly join or leave a union. Indeed when discussing the data in Table 1 it can be noted that a slight drop in the proportion of individuals who are union members between 2008 and 2010. However, union membership has been falling from 2002 and the fall from 2008 to 2010 is in line with the downward trend observed across the studies time period. As the fall in membership is not out of line with what would be anticipated based on trend, it is assumed that union membership has also been unaffected by the recession.

4.3 Generating the Counterfactual Input Series

When considering the counterfactual input series for unemployment the problem at hand is to generate the counterfactual unemployment rate which may have been observed had the 2008 economic crisis not occurred. In order to check the robustness of our preferred approach, in fact three alternative counterfactuals are generated. Therefore, while the autoregressive model outlined below, based on the approach used in FINGLETON and PALOMBI (2013), is the preferred method of generating the counterfactual unemployment rate the results of two alternative approaches to obtaining the counterfactual are also discussed below.

The preferred counterfactual series for unemployment rates in the NUTS1 regions are based on a panel autoregressive model in first differences fitted to data provided by Eurostat Regio, which includes region specific effects as shown in equation (4):

$$\Delta U_{rt} = \gamma_r + \sum_{j=1}^{2} \pi_j \Delta U_{rt-j} + \nu_{rt}; \forall r, t \tag{4}$$

In (4), ΔU_{rt} is the (differenced) log unemployment rate for region *r* in time period *t*, and ΔU_{rt-j} denotes lagged values for region *r* with lag *j* equal to 1 to 2. Also γ_r is the time invariant fixed effect for region *r* and ν_{rt} is the error term for region *r* and time *t*.[vi] Equation (4) is estimated for unemployment using annual data for 2001 to 2008 and used to generate the forecasted values for the unemployment rate in 2008 to 2010 using dynamic forecasting. This gives an estimate of what the unemployment rate in each region would have been had the 2008 economic crisis not occurred. These counterfactual predictions of the regional unemployment rates are used as the values for $\overline{U}_{r2010}$ in equation (3) when generating the no recession counterfactual $\overline{E}_{i2010}$.

The second counterfactual series is generated based on average annual growth rates in the time period leading up to the 2008 crisis. These are obtained by initially calculating the average annual change in the unemployment rate over the 2001 to 2008 period[vii]. Then it is assumed that this average annual rate of change would have continued into the future over the crisis period. Specifically, beginning with the 2008 rate of unemployment and applying the average annual growth rate over the 2001 to 2008 period, it is possible to generate the 2009 counterfactual unemployment rate. The same is done for 2010, using this counterfactual 2009 unemployment rate and the average annual 2001-2008 growth rate.

The third and final counterfactual unemployment rate is based on the assumption that if the 2008 crisis had not occurred the *status quo* would have been maintained. In this case it is simply assumed that the unemployment rate that would have been observed in 2010 had the crisis not occurred would be the same as the 2008 unemployment rate.

The merits and limitations of these three alternative approaches to generating counterfactual regional unemployment rates are discussed in Section 5.3. The results of the analysis using these three alternatives are presented in Table 3. As the substantive results remain unchanged regardless of the type of counterfactual employed (as will be seen in Table 3) the authors are confident in the robustness of this analysis to reasonable alternative specifications of the counterfactual unemployment rate.

4.4 Generating a Resilience Index

The very simple measure of resilience used in this paper is what is called absolute resilience, which is simply equal to the difference between an individual's 'observed' probability of employment $\hat{E}_{it}$ and the individual's probability of employment coming from the no recession counterfactual $\bar{E}_{it}$, as shown by equation (5). Provided it is negative, the larger the difference, the less resilient the individual.

$$r_{it} = \hat{E}_{it} - \bar{E}_{it} \tag{5}$$

4.5 The Determinants of Employment Resilience

Given the resilience measure (5), attention now focuses on assessing the effect of individual and region-level factors on inter-individual resilience, thus

$$r_{it} = \alpha_0 + X_{it}\beta + \lambda U_{rt} + \rho W_r U_t + \mu_r + \mu_{it}; \forall i, t = 2010 \tag{6}$$

Apart from r_{it}, the terms X_{it}, U_{rt} and $W_r U_t$ are identical to those in equation (1), but equation (6) is estimated via OLS, given that in this case there is no restriction on the feasible range of the dependent variable and it is again assumed that the regressors are exogenous. Also in this case, considering equation (6) as a generalised linear model, the link function *F* is the identity and so can be omitted. For the purposes of inference, we assume that the errors μ_{it} are not independently distributed by (positively) correlated within clusters (regions). However allowing for this leads to more corrected standard errors and eliminates upward bias in t-ratios, and this allows a more appropriate analysis of the effect of the individual level and regional level variables on the resilience of individuals. Note also that within-cluster correlation is also allowed for in inference involving the probit models.

5. Data

5.1 The European Social Survey

The data used in this analysis is derived from the European Social Survey (ESS). This survey gathers information from individuals aged 16 plus resident in European countries about a variety of issues ranging from the political opinions to their individual socio-economic characteristics. This paper is specifically concerned with data relating to the socio-economic characteristics as well as the regional identifiers within the data. The surveys were carried out in 2002, 2004, 2006, 2008, 2010 and 2012 but the 2012 survey data has only been released for selected countries and therefore cannot be used in this analysis. Accordingly, the paper does not consider all European countries covered in the ESS, instead focusing on the 13 countries which were covered in each wave from 2002 to 2010 of the survey, namely Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Ireland, the Netherlands, Norway, Portugal, Sweden and the United Kingdom.

Table 1 summarises the survey data of relevance to this study, showing that across the years the proportion of sampled individuals who are employed varies around 64% to 65% with the exception of 2010 where there was a drop of nearly 4 percentage points (which can be attributed to the economic crisis). Table 2 contains some indication of the varying interest in the survey across countries. Ireland, with about 4 million people, submitted more returns than the UK, with about 70 million. Thus the proportions in Table 1 are not true indications of the proportions in Europe as a whole. Nevertheless the survey as a whole amounts to about 25,000 individuals each year, or about 125,000 individuals overall, which is a large sample by most standards. Regarding the representativeness of the ESS, the sampling frame is the entire population of each country aged 16 and over. Random probability sampling is used to avoid bias. Each individual year of the ESS has a corresponding report on the representativeness of the sampling method. As an example, the ESS 2010 results are compared with the European wide Labour Force Survey (LFS) in KOCH et al. (2014) to assess its representativeness of the countries surveyed.

[insert Table 1 around here]

Table 2 shows the number of respondents in each country and the number of NUTS1 regions per country.

[insert Table 2 around here]

5.2 The NUTS1 Regions

Note that the administration of the survey in each country is based on differing degrees of geographic disaggregation. Countries that are part of the NUTS nomenclature have a regional variable that is possible to map to the NUTS system. Some countries use NUTS 1, but others NUTS 2 or 3. The data are therefore collected at different geographical levels for each country. The level of disaggregation used also varies within countries across years. Unfortunately, as noted by ROZANSKA-PUTEK et al. (2009) this means that finding a common geographical level when combining the ESS across countries and time is problematic. Indeed they note that the lowest level of disaggregation possible is at the NUTS1 level, which is the highest, sub-national, level of regional classification used by the European Union. Ideally, lower levels of geographical disaggregation would be used but this is not possible when combining the ESS across countries. Therefore, this paper uses NUTS1 regions in the analysis with Appendix 3 detailing the names of NUTS1 regions in each country considered.

In an analysis of the impact of the changing economic environment over the period of the 2008 economic crisis on the likelihood of an individual being employed (controlling for their individual level characteristics), it is reasonable to suppose that higher rates of unemployment at the NUTS1 regional level will have a negative effect on the likelihood of an individual being employed, since he or she will be faced with a crowded labour market characterised by a relatively high level of surplus labour. This is the motivation for using data on regional unemployment statistics at the NUTS1 level, as are available from Eurostat Regio.

5.3 The Counterfactual Input Series

Three alternative counterfactual series are presented. The first is what is termed the AR counterfactual, which represents the counterfactual derived from an autoregressive time series model based on the 2001 to 2008 data available for each individual region. The second is based on carrying forward the average annual growth rate of a region from the 2001 to 2008 period over the years to 2010. The third is based on an assumption that the rate of unemployment would have remained the same. For this the unemployment rate is set at the 2008 level of unemployment. Appendix 4 illustrates the no recession counterfactual series for the unemployment rate, in this case for all the major city regions of the sample (a major city region is the region in which the capital city of the country is located).

Each of these measures comes with advantages and disadvantages. In the case of the autoregressive models this has the advantage of generating dynamic forecasts based on the actual evolution of the data over the time period studied. However, the main drawback is that the relatively short time period leaves few degrees of freedom and raises questions as to the robustness of the forecasted counterfactual unemployment levels. The second approach of using the average annual growth rate and assuming that this continues post 2008 has the advantage of looking at the trend in the data and assuming this continues forward. However, the disadvantage is the average annual growth rate is based on the first and last year of the data and may be subject to these values not being representative of the time period overall. The final method has the advantage of simplicity, in that it is simply assuming that the *status quo* would continue. However, the disadvantage is that it is a big assumption to assume that the 2008 level of unemployment would not have changed if the crisis had not occurred, as the previous indicators show constant change over the 2001 to 2008 period. Therefore, to ensure robustness all three measures are employed and all three yield similar results. The reason similar results may be observed is that, even though all three counterfactuals are based on differing assumptions and calculations, the correlation coefficients between them are very high.

Between the AR and average annual growth rate the correlation is 0.93. Between the AR and 2008 level measures the correlation coefficient is 0.96. Finally between the average annual growth rate and 2008 level measure the correlation coefficient is 0.87.

6. Empirical Results

Table 3 gives parameter estimates based on equation (1) and on the four waves of data, for 2002, 2004, 2006 and 2008 (giving approximately 25,000 observations per wave). Model (1) relates to the probit estimation of equation (1). Model 2 involves instrumental variable probit estimation of equation (1) using the three group method and LE GALLO and PAEZ (2013) synthetic instruments to instrument the unemployment rate. In order to assess whether endogeneity is an issue in the estimation method adopted the Wald endogeneity test is used (STATA, 2009). The null hypothesis for this test is that the specified variable (in this case the regional unemployment rate) is not endogenous. When this test is applied a p-value of 0.2385 is obtained, which indicates that there is not sufficient evidence to reject the null hypothesis in favour of the alternative hypothesis of endogeneity. The results suggest that the estimates from Model (1), the standard probit model, are consistent and not biased. Therefore, this paper proceeds with interpreting the estimates from Model 1 (while also presenting Model 2, the IV probit estimation, for completeness).[viii]

As expected, both individual level and regional level variables impact on the probability of employment to varying degrees. It appears that younger individuals are more likely to be employed relative to those in the age category >65, with those aged between 25-34, 35-44 and 45-54 being the most likely to be employed. Regarding educational attainment, relative to those with *less than lower secondary education*, individuals with *post-secondary non-tertiary education completed* and *tertiary education completed* are the most likely to be employed. Union members have a higher probability of being employed than non-union members, and the probability of employment increases if one is a male. Also the greater the number of people in the household, the more likely the respondent is to be employed, although this is not a significant effect.

From a regional perspective, having controlled for individual-level variables, there is evidence that the regional economy has a separate and significant impact on individuals' employment probabilities. Individuals living in regions with a high rate of unemployment tend to have a lower individual employment probability. This can be interpreted as the net outcome of labour demand and supply effects, in line with BAUM and MITCHELL (2010). While the region of residence has a significant effect, the spatial lag of the unemployment rate this is statistically insignificant. This indicates that the labour market in neighbouring regions does not impact on an individual's probability of employment in a given region.

Due to space constraints we do not present our regional fixed effects in Table 3. However, these results shows that, relative to the 'Belgium effect' (NUTS1 region BE1), being a resident of Denmark and Finland tends to lower the employment probability, while being resident in Portugal, Spain and Switzerland increases it. The regional dummies, on balance and across the models, show little difference between the regions of France, Germany, the Netherlands, Norway, the UK and the reference category Belgium, with effects mainly insignificantly different from zero. The higher employment probabilities associated with regions in Spain and Portugal reflect the unsustainable growth in these economies at a time (2002 to 2008) when capital was freely available and demand was high due to boom conditions in local and international economies.

[insert Table 3 around here]

6. Individual Employment Resilience

Table 4 gives the estimates from equation (6), with the focus now being on the effect on individual level resilience of individual level characteristics, namely education, union membership and age. As the Wald test of endogeneity indicates that the unemployment rate is exogenous, estimation is via OLS rather than instrumental variable techniques. As there are three alternative measures of the counterfactual unemployment rate, three separate sets of estimates are given in Table 4. The first column is based on the resilience index calculated using the AR counterfactual unemployment rate series. The second column is based on the resilience index calculated using the average annual growth rate counterfactual unemployment rate series. The final column of results is based on the resilience index calculated assuming that the 2010 unemployment rate would equal the 2008 unemployment rate. The only significant change in the results across these three alternatives is that under the second and third assumptions the age 35-44 coefficient is significant and positive. While the values of the other coefficients obviously vary according to how the counterfactual unemployment rate was calculated, the sign and significance of the variables do not change, suggesting that the results are reasonably robust.

Regarding age, it is evident that those whose probability of employment has been least affected by the crisis fall into the middle aged category, with those aged 3*5-44* the most resilient (in two of the models). In contrast, people at the extremes of the age spectrum have been affected more, so that younger individuals (in model 1) and older individuals come out as relatively less resilient (in model 2 and 3).

Table 4 also indicates that those with higher levels of educational attainment are more resilient than those with less education. *Tertiary education* is the most important factor enhancing resilience to the economic crisis. Tertiary education appears to convey a dual benefit to individuals; increasing their probability of employment (as seen in Table 3) while also increasing their resilience to economic shocks (as seen in Table 4). Post-secondary (but non tertiary) education conveys an advantage in terms of employment probability but does not appear to impart resilience to shocks. When considering gender, men turn out to be more resilient than women. This possibly reflects differences in terms of tenure of employment, with many women on part-time contracts or more recent entrants into the workforce, so that their employment proved easier and less costly to terminate than full time posts. Finally, union membership conveys resilience to individuals increasing their resilience compared to those who are not in a union. This is despite the fact that many public sector jobs are unionised, and it is the public sector which has taken the direct impact of Government inspired austerity measures in most countries.

It is also evident that living in a high unemployment region reduces individual resilience. This can be linked with the initial finding (Table 3), which was that, *ceteris paribus*, a tougher regional labour market would make it less likely for an individual to obtain employment. Therefore, individuals in regions with high level of unemployment are less likely to be employed and are also less resilient during a crisis. Moreover, in contrast to the employment probability analysis, there is a significant positive effect for the spatial lag of the unemployment rate. This suggests that there are spillovers among regional labour markets when considering resilience. Interestingly, a region which tends to be bordered by higher unemployment regions is likely to possess individuals which are relatively more resilient. This may capture the sorting effect mentioned in Appendix 2, where more resilient individuals sort from poorly performing regions to regions which possess better labour markets.

[insert Table 4 around here]

7. Conclusions

This paper analyses the resilience of individual employment to the 2008 economic crisis taking into account not only the evolution of the regional economy in which the individual resides, but also individual-specific characteristics. In doing so it is among the first to consider resilience from the perspective of the individual rather than an aggregate measure of employment or output at a regional level while also considering the role played by regional factors, captured by the regional unemployment rate variable, in determining the individual's likelihood of employment. This two-level approach leading to counterfactual analysis is the main innovatory contribution of the paper.

The analysis is accomplished through the use of five waves of the European Social Survey (ESS) which is a repeated cross-sectional survey conducted across European countries. The paper models employment outcomes for individuals using the 2002, 2004, 2006 and 2008 waves of the ESS and subsequently generates predicted employment outcomes for individuals using the actual economic conditions in 2010 and then by using no-recession counterfactual assumptions about regional unemployment. Thus it predicts individuals' employment probabilities on the basis of actual economic conditions experienced through the recession and on the basis of hypothetical data assuming that the crisis did not occur. It then generates a measure of resilience based on the difference between 'actual' and counterfactual employment outcomes.

The paper finds that there is significant regional variation in the employment resilience of individuals. While employment outcomes in regions in Ireland, Spain and Portugal were higher in the pre-2008 period relative to German and French regions (among others), post 2008 it is observed that Spanish and Portuguese regions had lower levels of employment resilience relative to French and German regions. The majority of regions' actual employment outcomes were below the counterfactual prediction, however there is substantial heterogeneity with some regions being far more adversely affected than others. Notwithstanding heterogeneity, there is a large degree of spatial correlation in resilience, with Central European regions proving relatively more resilient than peripheral regions, with instances of low resilience increasing as distance from Germany and Eastern France increased, so that the regions of Ireland, Spain and Portugal were the most adversely affected.

Regarding the individual factors which drive resilience, having controlled for region level factors via the regional dummies and the regional unemployment rate, it is noted that more educated individuals prove more resilient than those with lower levels of education, suggesting that not only does higher levels of education increase the probability of an individual being employed (see Table 3) but that it also increases their employment resilience during periods of economic crisis (see Table 4). Likewise middle age individuals as well as those in a union are more resilient than younger and older individuals or those not in a union.

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Table 1: Descriptive Statistics by Year

Variable	2002	2004	2006	2008	2010
Employed	65.38%	64.16%	64.81%	64.21%	61.53%
Age Category					
16-24	11.58%	11.63%	10.93%	10.84%	11.96%
25-34	15.76%	15.33%	15.04%	14.78%	13.92%
35-44	19.86%	19.01%	18.46%	17.87%	16.84%
45-54	16.75%	16.52%	16.63%	16.95%	17.36%
55-65	15.34%	15.92%	16.39%	16.10%	16.36%
>65	20.09%	20.91%	21.95%	22.77%	22.80%
Education					
Less than lower secondary education	17.29%	18.98%	18.17%	17.81%	17.71%
Lower secondary education completed	20.02%	19.75%	18.28%	17.93%	18.43%
Upper secondary education completed	35.72%	33.35%	32.92%	32.29%	30.35%
Post-secondary non-tertiary education completed	1.88%	2.20%	2.86%	2.70%	4.52%
Tertiary education completed	24.91%	25.27%	27.76%	29.24%	28.62%
Individual Specific Factors					
Union Membership	27.17%	25.40%	24.13%	23.27%	22.44%
Female	52.05%	53.45%	53.21%	52.58%	52.39%
Number of People in Household	2.69	2.67	2.61	2.58	2.60

Source: (ESS ROUND 1: EUROPEAN SOCIAL SURVEY ROUND 1 DATA, 2002; ESS ROUND 2: EUROPEAN SOCIAL SURVEY ROUND 2 DATA, 2004; ESS ROUND 3: EUROPEAN SOCIAL SURVEY ROUND 3 DATA, 2006; ESS ROUND 4: EUROPEAN SOCIAL SURVEY ROUND 4 DATA, 2008; ESS ROUND 5: EUROPEAN SOCIAL SURVEY ROUND 5 DATA, 2010)

Table 2: Sample Size by Country

Country	Number of Observations					Number of NUTS1 Regions
	2002	2004	2006	2008	2010	
Belgium	1,871	1,760	1,779	1,737	1,689	3
Denmark	1,506	1,474	1,505	1,595	1,556	1
Finland	1,968	1,994	1,870	2,172	1,846	1
France	1,498	1,798	1,973	2,058	1,707	8
Germany	2,905	2,851	2,900	2,740	3,001	16
Ireland	2,045	2,282	1,795	1,757	2,556	1
Netherlands	2,351	1,871	1,886	1,766	1,815	4
Norway	2,036	1,744	1,731	1,534	1,526	1
Portugal	1,494	2,044	2,211	2,359	2,144	1
Spain	1,713	1,658	1,872	2,560	1,882	7
Sweden	1,977	1,922	1,911	1,807	1,486	3
Switzerland	1,990	2,131	1,796	1,811	1,497	1
UK	2,043	1,771	2,379	2,337	2,340	12

Table 3: Results of PROBIT Estimation of Equation (1), probability of employment

Variable	Model 1	Model 2
Constant	-0.4355*	-0.2275
	(0.2675)	(0.4475)
Age Category		
16-24	1.5867***	1.5866***
	(0.0664)	(0.0664)
25-34	1.6989***	1.6986***
	(0.0672)	(0.0675)
35-44	1.7708***	1.7710***
	(0.0804)	(0.0803)
45-54	1.6942***	1.6942***
	(0.0932)	(0.0934)
55-65	0.9712***	0.9710***
	(0.0880)	(0.0880)
Education		
Lower secondary education completed	-0.0236	-0.0235
	(0.0333)	(0.0333)
Upper secondary education completed	0.0352	0.0356
	(0.0353)	(0.0351)
Post-secondary non-tertiary education completed	0.1493***	0.1489***
	(0.0444)	(0.0446)
Tertiary education completed	0.3240***	0.3241***
	(0.0395)	(0.0394)
Individual Specific Factors		
Union Membership (1/0)	0.5095***	0.5091***
	(0.0571)	(0.0568)
Female	-0.1670***	-0.1669***
	(0.0291)	(0.0291)
Number of People in Household	0.0179	0.0177
	(0.0116)	(0.0117)
Regional Unemployment rate	-0.0306***	-0.0462***
	(0.0149)	(0.0291)
W*Regional Unemployment rate	0.0018	0.0084
	(0.0090)	(0.0170)
Year		
2002	-0.0082	-0.0083
	(0.0425)	(0.0417)
2004	0.0006	0.0078
	(0.0396)	(0.0422)
2006	0.0305	0.0346
	(0.0352)	(0.0362)
Obs	102,075	102,075

Log-Likelihood	-49512	-159378
Pseudo R2	0.2543	na

Note 1: Dummy variables representing the NUTS1 region the individual is located in are included. The coefficients of these regional controls are excluded due to space constraints but include a discussion of them in the paper.

2: ***, ** and * indicate significance at the 99, 95 and 90 percent levels

3: Model 1 is the probit estimation of equation (1), Model (2) is the instrumental variable probit estimation of equation (1) using Bartlett's three group method and LE GALLO and PAEZ (2013) synthetic instruments to generate instruments to control for potential endogeneity.

4: The p-value for the Wald test of endogeneity for Model 2 is 0.2854. This suggests that the unemployment rate is exogenous.

5: The standard error estimates are corrected for intra-cluster correlation with respect to NUTS1 regions.

Table 4: Estimates of equation (6), Individual Resilience

Variable	Model 1	Model 2	Model 3
Constant	0.1968***	-0.0050	-0.0027
	(0.0020)	(0.0045)	(0.0045)
Age Category			
16-24	-0.0054***	-0.0050	-0.0050
	(0.0025)	(0.0036)	(0.0036)
25-34	-0.0016	0.0046	0.0048
	(0.0022)	(0.0035)	(0.0035)
35-44	0.0001	0.0086***	0.0089***
	(0.0020)	(0.0036)	(0.0036)
45-54	-0.0022	0.0038	0.0040
	(0.0023)	(0.0035)	(0.0036)
55-65	-0.0128***	-0.0260***	-0.0263***
	(0.0037)	(0.0040)	(0.0041)
Education			
Lower secondary education completed	-0.0015	-0.0018	-0.0018
	(0.0010)	(0.0019)	(0.0019)
Upper secondary education completed	-0.0007	-0.0013	-0.0013
	(0.0009)	(0.0018)	(0.0018)
Post-secondary non-tertiary education completed	0.0009	0.0025	0.0026
	(0.0010)	(0.0020)	(0.0020)
Tertiary education completed	0.0034***	0.0076***	0.0078***
	(0.0011)	(0.0020)	(0.0021)
Individual Specific Factors			
Union Membership (1/0)	0.0066***	0.0153***	0.0156***
	(0.0020)	(0.0025)	(0.0026)
Female	-0.0012***	-0.0030***	-0.0030***
	(0.0004)	(0.0006)	(0.0006)
Number of People in Household	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
Regional Unemployment rate	-0.0124***	-0.0074***	-0.0076***
	(0.0001)	(0.0001)	(0.0001)
W*Regional Unemployment rate	0.0013***	0.0013***	0.0013***
	(0.0001)	(0.0001)	(0.0001)
Obs	24,952	24,952	24,952
R2	0.9237	0.8667	0.8656

Note 1: Dummy variables representing the region the individual is located in are included. The coefficients of these regional controls are excluded due to space constraints but include a discussion of them in the paper.

2: ***, ** and * indicate significance at the 99, 95 and 90 percent levels

3: Model 1 is the probit estimation of equation (6) when our resilience index is based on our AR unemployment rate counterfactual. Model 2 is when our resilience index is based on our average annual growth of the unemployment rate counterfactual. Model 3 is when our resilience index is based on the assumption that the unemployment rate in 2010 remains the same as the rate in 2008.

4: The standard error estimates are corrected for intra-cluster correlation with respect to NUTS1 regions.

Appendix 1

Table 1: Summary of Existing Methodologies and Results

Type of Study	Method Used	Area of Analysis	Results	Authors
Case Study	Qualitative analysis. Interviews with regional agents. Policy analysis.	Munich	Resilient economy due to strong knowledge institutions, innovation systems and networks.	Evans and Karecha (2014)
Indices	Resilience and recovery indices measure the initial impact of a crisis and subsequent recovery.	UK Regions	The lower a region's resistance to a recession, the slower the region's subsequent rate of recovery.	Martin (2012)
		US Cities and Counties	Differences in resilience explained by varying industry structure. Manufacturing concentration promotes resilience.	Augustine, Wolman et al. (2013)
Time Series Analysis	Statistical time series models such as VAR and VEC models are utilised.	UK Regions	National shocks had a permanent effect on the growth path of employment within regions.	Fingleton, Garretsen et al. (2012)
		European Countries	Shocks to GDP had a permanent effect on productivity levels across European countries.	Doran and Fingleton (2014)
Formal Economic Models	Spatial panel models are utilised.	UK Cities	Hysteretic effects are found to be present but industry structure can aid in explaining resilience.	Fingleton and Palombi (2013)

		US Cities	Hysteretic effects are found to be present but factors such as size and sectoral concentration effect resilience.	Doran and Fingleton (2013)
Pooled Individual Data	Pooled probit and regression models are utilised.	US Regions	Shocks impact individual wages but different regional and individual level factors can aid in explaining resilience.	Doran and Fingleton (2015)

Based on Martin and Sunley (2014) Table 4 pg 17

Appendix 2 – Endogeneity

Endogeneity bias could occur if there are one or more omitted variables causing the error term to be correlated with the regressors included in the model, as would be the case if included and omitted variables were correlated. This is a consideration because in the case of this paper the size and significance of the regional unemployment variable could possibly be biased by the existence of an omitted variable(s) correlated with the regional unemployment rate. We have tried to avoid omitting variables by the presence of the regional fixed effects and also by the inclusion of the spatial lag term $W_r U_{rt}$ and, as it turns out, this is not an issue for us but it is useful to rehearse the arguments. Typically an important source of endogeneity is the existence of sorting, which has been suggested as a potentially real phenomenon in the economic geography literature, for example we could see sorting into high amenity or network-rich, urban locations (Venables 2011), and we can also envisage sorting based on regional labour market conditions. Sorting is a phenomenon well known, for example, in the educational economics literature. An instance would be where one is trying to analyse the effect of class size on pupil performance, but parents opt to place high ability pupils non-randomly into smaller classes, so that small class pupils perform better because they have more ability, which is omitted from the analysis, and not because small class size per se has an effect. In this case, ability is an omitted variable which is correlated with class size and causes omitted variable bias in the class size parameter. Therefore, in the context of the analysis, a low unemployment rate in a region may stimulate the sorting of highly educated, mobile individuals into the region. Although the basis of the analysis is a detailed empirical model capturing individual and regional effects on the probability of employment, and so hopefully capturing the main determinants of employment and resilience in the models, we nevertheless take a cautionary approach, mindful of the possibility of a sorting effect. In other words sorting due to omitted variables could theoretically be an issue because we are not able to control for individual unobservables via fixed or indeed random effects (which is not possible given the data). Accordingly, in the ancillary instrumental variable probit model estimation summarised in Table 5 we have endeavoured to control for endogeneity due to omitted variables using instruments while also including regional fixed effects to control for omitted variables at the regional level.

It is difficult to identify suitable instruments for inclusion in the model, and we therefore adopt Bartlett's three group method (initially introduced in the context of endogeneity caused by measurement error) as an instrument for the unemployment rate. BARTLETT's (1949) three group method was proposed as a more efficient instrumental approach than the Wald method. It divides the endogenous variable into three categories based on the size of the variable. The n/3 smallest are set to -1, the n/3 largest are set to 1 and the n/3 middle values are set to zero (Johnson 1984, Kennedy 2008). The process was initially designed to address measurement error but can be applied in the context of endogenous regressors (Fingleton 2003, Artis, Miguelez et al. 2012, Le Gallo and Paez 2013). While it appears to be a feasible and easy to implement solution, we remain cautious, since FINGLETON and LE GALLO (2007) show that three-group instruments which are based on an endogenous variable will retain an unwanted element of correlation with the residuals, thus perhaps reducing endogeneity-induced bias, but maybe not totally eliminating it. We also include an additional set of instruments based on the synthetic instruments approach developed in Le Gallo and Paez (2013). They outline a five step procedure which produces a synthetic instrument for each endogenous variable. We briefly outline their approach here but refer interested readers to the full explanation in Le Gallo and Paez (2013). It starts by defining a contiguity matrix, in the case of this paper a matrix of inter-NUTS1 regional contiguity, and obtaining the eigenvectors of this matrix. Then each eign-vector is regressed on the endogenous variable and the significant eigenvectors are retained and summed to create an exogenous instrument (each significant eign-vector is weighted according to the regression coefficient obtained by regressing the eign-vector on the endogenous variable). This is done separately for each time period, with the set of instruments then concatenated to create a single instrument covering all periods.

Therefore, in total we estimate two models based on equation (1). The first is estimated using a standard probit model, and the second controls for possible endogeneity via an instrumental variable probit model. However the test of endogeneity and the estimates obtained point to the standard probit model as an appropriate vehicle for analysis.

Appendix 3

NUTS1 Regions Used

NUTS1 Code	Region Name	NUTS1 Code	Region Name
BE1	Région de Bruxelles-Capitale	FR1	Île de France
BE2	Vlaams Gewest	FR2	Bassin Parisien
BE3	Région wallonne	FR3	Nord - Pas-de-Calais
CH	Switzerland	FR4	Est (FR)
DE1	Baden-Württemberg	FR5	Ouest (FR)
DE2	Bayern	FR6	Sud-Ouest (FR)
DE3	Berlin	FR7	Centre-Est (FR)
DE4	Brandenburg	FR8	Méditerranée
DE5	Bremen	IE0	Éire/Ireland
DE6	Hamburg	NL1	Noord-Nederland
DE7	Hessen	NL2	Oost-Nederland
DE8	Mecklenburg-Vorpommern	NL3	West-Nederland
DE9	Niedersachsen	NL4	Zuid-Nederland
DEA	Nordrhein-Westfalen	NO	Norway
DEB	Rheinland-Pfalz	PT1	Continente
DEC	Saarland	SE1	Östra Sverige
DED	Sachsen	SE2	Södra Sverige
DEE	Sachsen-Anhalt	SE3	Norra Sverige
DEF	Schleswig-Holstein	UKC	North East (UK)
DEG	Thüringen	UKD	North West (UK)
DK0	Danmark	UKE	Yorkshire and The Humber
ES1	Noroeste (ES)	UKF	East Midlands (UK)
ES2	Noreste (ES)	UKG	West Midlands (UK)
ES3	Comunidad de Madrid	UKH	East of England
ES4	Centro (ES)	UKI	London
ES5	Este (ES)	UKJ	South East (UK)
ES6	Sur (ES)	UKK	South West (UK)
ES7	Canarias (ES)	UKL	Wales
FI1	Manner-Suomi	UKM	Scotland
		UKN	Northern Ireland (UK)

Appendix 4

Actual and Alternative Counterfactual Unemployment rates for EU NUTS0 Capital Regions

NUTS0	Actual Unemployment	AR Counterfactual Unemployment	Average Annual Growth Rate Unemployment	2008 Unemployment
BE1	17.30%	15.75%	19.85%	15.90%
CH	4.50%	3.44%	4.35%	3.30%
DE3	13.20%	14.76%	18.84%	15.20%
DK0	7.50%	3.69%	3.50%	3.40%
ES3	16.10%	5.98%	4.27%	8.70%
FI1	8.40%	6.33%	4.96%	6.40%
FR1	8.90%	7.51%	7.83%	7.20%
IE0	13.90%	4.41%	4.78%	6.00%
NL1	4.90%	3.58%	3.76%	3.40%
NO0	3.50%	2.18%	2.24%	2.50%
PT1	11.00%	7.78%	15.17%	7.70%
SE1	8.20%	5.71%	7.95%	5.90%
UKI	9.00%	5.87%	6.37%	7.10%

Note 1: AR Counterfactual refers to the counterfactual unemployment rate derived from the autoregressive model outlined in Section 4.3. The average annual growth rate unemployment counterfactual refers to the counterfactual based on the average annual growth rate from 2001 to 2008. The 2008 unemployment rate is based on the assumption that the unemployment rate would not have change from 2008 to 2010 had the crisis not occurred.

Appendix 5 – Sub Sample of Germany, France, Spain and the UK

Variable	Probit - Employment	OLS - Resilience
Constant	-0.6485***	0.0164***
	(0.0741)	(0.0015)
Age Category		
16-24	1.7156***	-0.0017
	(0.0600)	(0.0012)
25-34	1.6770***	-0.0016
	(0.0475)	(0.0011)
35-44	1.7985***	0.0014
	(0.0512)	(0.0016)
45-54	1.7045***	-0.0016
	(0.0552)	(0.0011)
55-65	0.9286***	-0.0117***
	(0.0449)	(0.0031)
Education		
Lower secondary education completed	0.0379	0.0004
	(0.0363)	(0.0008)
Upper secondary education completed	-0.0128	0.0005
	(0.0373)	(0.0009)
Post-secondary non-tertiary education completed	0.1289***	0.0023
	(0.0487)	(0.0014)
Tertiary education completed	0.2970***	0.0044***
	(0.0347)	(0.0018)
Individual Specific Factors		
Union Membership (1/0)	0.5538***	0.0090***
	(0.0619)	(0.0028)
Female	-0.1333***	-0.0010***
	(0.0295)	(0.0005)
Number of People in Household	0.0090	-0.0002
	(0.0082)	(0.0001)
Regional Unemployment rate	-0.0278***	-0.0056***
	(0.0116)	(0.0000)
W*Regional Unemployment rate	0.0031	0.0014***
	(0.0149)	(0.0000)
Year		
2002	0.0552	na
	(0.0259)	
2004	0.0503	na
	(0.0299)	
2006	0.0668	na
	(0.0284)	
Obs	34,889	8,901

Log-Likelihood	-17358	na
Pseudo R2	0.2484	0.9354

Note 1: Dummy variables representing the region the individual is located in are included. We exclude the coefficients of these regional controls due to space constraints but include a discussion of them in the paper.
2: ***, ** and * indicate significance at the 99, 95 and 90 percent levels
3: We cluster the error term of the model based upon NUTS1 regions.
4: The probit estimation is comparable to Table 5 but with just the four countries included. The OLS equation is comparable to Table 6 but just based on the four countries included.

[i] NUTS translates as Nomenclature of Territorial Units for Statistics.
[ii] DORAN and FINGLETON (2014) focus their analysis on productivity but discuss the impact of output shocks on the two facets of productivity; output and employment.
[iii] Note that when there are variables at different levels of aggregation, such as regional and individual, there is a possibility that the estimated standard errors are biased, as pointed out by MOULTON (1990). In order to correct for this bias the error terms are clustered by region. This is discussed in more detail in Section 4.
[iv] . This would be an ideal situation because then this paper would be accounting for much inter-individual variation and reducing bias due to omitted variables.
[v] The model is estimated in Stata 11 and uses the ivprobit command.
[vi] Note that since ΔU_{rt} is the first difference of log unemployment, it equates to exponential rates of growth
[vii] The average annual growth rate is calculated as $g = \left(1/T\right) * \ln\left(U_{t+T}/U_t\right)$
[viii] Note that as Germany, France, Spain and the UK account for the majority of the regions considered the authors re-run our analysis using these four countries as a sub sample to test the robustness of our results. What is observed is that the results from our alternative sub-sample are consistent with the full sample results presented in Sections 6 and 7. The alternative sub-sample estimates are presented in Appendix 5.