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Technological Coherence and the Adaptive Resilience of Regional Economies

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TECHNOLOGICAL COHERENCE AND THE ADAPTIVE RESILIENCE OF REGIONAL ECONOMIES

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ABSTRACT

This paper explores the effect of different regional technological profiles on the resilience of regional economies to exogenous shocks. We conduct an empirical examination of the determinants of resilience through panel analyses of UK NUTS III level data for the 2004-2012 period. The results indicate that regions endowed with technologically coherent – and not simply diversified – knowledge bases are better prepared to face an unforeseen downturn and display resilience. Moreover, local economies tend to be more adaptable if they innovate in sectors with the strongest growth opportunities, even though firms' net entry does not appear to contribute significantly towards resilience.

JEL codes: O30, R11, O33.

Keywords: resilience, adaptation, innovation, technological variety, financial crisis.

1. Introduction

In the context of recovery from the Great Recession the concept of adaptive resilience has gained traction in the literature. Adaptive resilience involves the capacity of a regional economy to absorb the effects of recessionary forces and the ability of its industrial and technological structure to react to exogenous shocks through adaptation and innovation (Martin, 2012). The evolution of regional economies is uneven (Saxenian, 1994; Porter 2003; Gardiner et al., 2014) and inter-regional differences can become even sharper when tested by downturns (OECD, 2014; Dijkstra et al., 2015). Some regions appear to be more adaptable and able to absorb shocks while others experience decline. What can explain the differential performance of regions after and during a crisis? Martin (2012) argues that adaptive resilience depends on factors such as: the formation of new firms, innovation, willingness to change, the diversity of regional economic structures and the availability of skilled labour. Related studies (among others: Davies and Tonts, 2010; Essletzbichler, 2015; Boschma, 2015) have identified variety as an especially important driver of resilience.

In the economic literature the more general relation between variety and regional growth has been approached in several ways. Attaran (1985) treated variety as a portfolio diversification strategy that protects regions from exogenous shocks. A higher degree of sectoral diversification could therefore alleviate the negative impact of a crisis on employment. In considering regional growth dynamics in the long run, Pasinetti (1993) argued that an economy must increase variety over time in order to generate productive gains and limit structural unemployment due to a combination of product innovation and technical progress in production. Variety in complementary industries or technologies can trigger knowledge spillovers capable of absorbing the effect of downturns (Glaeser, 2005). However, the development and exploitation of positive externalities may be more efficient when growth opportunities are consistent with the existing knowledge base and when processes of knowledge recombination involve technologically related inputs (Fleming,2001; Frenken et al., 2007; Antonelli et al., 2010).

In this paper we theorise and test what kind of technological diversification drives adaptive resilience. To the best of our knowledge not many studies attempt to measure, estimate and explain regional adaptive resilience, which is often treated as a latent quality of a local economic system. We address this gap by means of econometric analyses of a panel of 134 English NUTS III regions covering the 2004-2012 period. We combine employment and industry data from the UK Office for National Statistics (ONS) with information extracted from the European Patent Office (EPO)'s PATSTAT database, grouping patents into 8 technological classes and 121 sub-classes according to the International Patent Classification (IPC). As we want to analyse the impact of different types of technological diversification on resilience, we use information on inventor location and 3-digit technology codes to calculate different measures of diversification. The econometric evidence uncovers the crucial role of technological coherence. It also suggests that regions that innovate in high-tech sectors tend to be more resilient while the effect of new firms' entry is overall negligible.

The paper is structured as follows. In section 2 we review the literature on adaptive resilience and profile the theoretical line of the paper. In section 3 we present the data, the construction of diversification indices, and the variables included in the modelling exercise. In section 4 we present the estimation strategy and results. We discuss our main findings then conclude in Section 5 with reference to their implications for future research.

2. Literature Review

2.1 What is resilience?

The concept of resilience has been used in different contexts and with different connotations (Reggiani et al., 2002; Christopherson et al., 2010). This has generated some conceptual ambiguity that has often made its operationalisation for empirical testing difficult. 'Resilience' has been be viewed from at least three different perspectives: engineering, ecological and adaptive. Earlier studies on 'engineering resilience' focused on the stability of a system working closely to equilibrium or a steady state, while 'ecological resilience' denotes the capacity of a system 'to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity and feedbacks' (Walker et al, 2006: p.2).

A more recent interpretation of the concept as 'adaptive resilience' has been proposed in relation to the region's ability to reorganise economic structures to absorb the effect of a destabilising shock (Martin, 2012). Resilience involves the regional economies' capacity to recover from an unexpected downturn as well as the capacity to reconfigure productive activities and develop new growth paths (Boschma, 2015). According to this literature resilience does not simply entail the return to a stable equilibrium state (Simmie and Martin, 2010) but rather the regional economy's ability to adapt to change through innovation (Saviotti, 1996; Crescenzi et al., 2016).[1]

In evolutionary terms (Boschma and Frenken, 2006; Boschma and Martin, 2007) adaptation can be conceptualised as a path-dependent process shaped by the regions' endogenous pre-shock characteristics and by the regional systems ability to recombine knowledge towards emerging technological fields so as to maintain satisficing growth paths in output and employment over time. Adaptive resilience, therefore, is not a static characteristic of the region but involves a localised process of Schumpeterian change in which 'pre-existing resources and capabilities often shape new growth paths, as these are rejuvenated and redeployed in new combinations' (Boschma, 2015: p. 736). This is consistent

[1] For an in-depth discussion of the notions of resilience and equilibrium in dynamic economic systems, see Reggiani et al. 2002.

with a recombinant approach to growth whereby economic development consists in using known resources in a different way to realise new things with them (Weitzman, 1998).

Despite growing scholarly interest, comprehensive empirical evidence on the determinants of resilience is still scant. Martin (2012) provides useful guidance by developing the idea that adaptive resilience depends on a mix of factors such as entrepreneurship, the firms' willingness and ability to react to or trigger change, and the technological and skills endowments of the region. In his exploratory analysis of UK NUTS 1 regions Fingleton (2012) confirms that in order to explain resilience one should look at a region's prior economic performance, the structure of the economy, and the region's innovation system (including the skills base and entrepreneurial culture).

2.2 The sources of regional resilience

The first conjecture is that variety of economic activities prompts resilience and shapes a region's capacity to absorb the negative effects of a downturn (Fingleton et al 2013; Boschma, 2015). Jacobs (1969) already proposed that the exchange of cross-sectoral knowledge promotes externalities that foster innovation and trigger localised growth. A high degree of variety should favour the generation of spillovers and open up opportunities for the pursuit of new activities (Glaeser et al., 1992; Feldman and Audretsch, 1999). Attaran (1985) and Frenken et al. (2007) argue that broader portfolio diversification can protect local labour markets from destabilising factors (e.g. workers that have been made redundant could be absorbed by industries that are relatively less affected by a downturn) and Boschma (2015) adds that local economies with higher degree of variety should be able to minimise the risks linked to idiosyncratic (sector-specific) shocks and therefore enhance adaptability.

Simmie and Martin (2010) suggest that regional resilience is co-determined by endogenous sources of new knowledge and by particular decisions about the use of this knowledge. The degree of technological coherence of a region's technology portfolio can favour knowledge spillovers because it lowers the barriers for novelty generation and exploitation (Frenken et al., 2007). Holm and Østergaard (2015) have recently shown that related technological variety positively influenced the resilience of the ICT sector in Denmark after the burst of the dot.com bubble. This is in line with empirical evidence suggesting that agglomeration economies of related sectors tend to favour the growth of clusters (Porter, 2003; Feldman and Audretsch, 1999; Delgado et al., 2014).

Regions that have diversified in technologically related sectors, where firms can share complementary know-how, may have an advantage in undertaking and exploiting processes of knowledge recombination within pools of existing knowledge, across pools of old and new knowledge, and arguably in different pools of new knowledge (Boschma and Iammarino, 2009).

Innovations that arise from recombinant processes are on average more successful due to the benefits of past experience: through time, actors learn to identify what elements to recombine, what to leave aside, and what combinations are better than others for specific contexts and strategic objective (Fleming, 2001; Fleming and Sorenson, 2001). In this process, recombination of related components tends to be associated with lower costs and lower levels of uncertainty of innovation outcomes. Therefore, during times of economic uncertainty proximity in the technology space might be as important as geographical proximity in that it is easier to utilise knowledge inputs that are coherent with one other compared to cognitively distant inputs (Noteboom, 2000; Boschma, 2005; Antonelli et al., 2010; Quatraro, 2011). It follows that during economic downturns a region with a comparatively higher number of technologically related activities can exploit more learning opportunities and is more likely to create new growth paths through the recombination of available technological competences (Boschma et al., 2012).

In the short run the regional economies' opportunities for path renewal are arguably stronger when a region's industrial structure exhibits a higher degree of related variety and stronger inter-industry learning (Frenken et al., 2007; Sedita, 2014). Regions can develop new developmental paths as new activities branch out from existing sectors on the basis of technologically related resources (Boschma, 2015). However, there is abundant empirical evidence that industries differ substantially in their innovation patterns, search and appropriability regimes, and demand (Breschi, Malerba, and Orsenigo, 2000; Malerba, 2006). This implies that the opportunities for growth are not evenly distributed across sectors and that the type of industry specialisation can have significant consequences in sustaining aggregate performance (Audretsch, 1995; Glaeser and Kerr, 2009; Diodato and Weterings, 2015). Local economies, therefore, might gain competitive advantage by orienting some productive capabilities towards emerging fields and new demand (Suire and Vincente, 2009). Other things being equal, we expect that regions will tend to be more resilient if they orient their innovative activities towards sectors with the strongest growth opportunities. High-tech sectors are areas of specialisation able to provide such growth opportunities even though these might entail greater technology risk (OECD, 2013).

One aspect of growth dynamics that has attracted not only considerable academic scrutiny but also strong policy interest is the role of entrepreneurship. Entrepreneurs can directly contribute to processes of economic development by identifying and capturing new business opportunities and by converting new knowledge into marketable products (Schumpeter, 1934; Baumol, 2010). New firms can therefore be powerful engines of structural change and positive contributors to regional growth (see, among others, Audretsch and Keilbach, 2004; Fritsch, 2007; Haltiwanger et al., 2013).[2] By starting new businesses,

[2] Van Praag and Versloot (2007), Frisch (2013) and Doran et al. (2016) provide extensive reviews of this research stream.

entrepreneurs capture locally available knowledge, shape the exploitation of resources in novel or more efficient ways, and in doing so have the potential to sustain local labour markets. New firms have been profiled as a key determinant of regional resilience because they provide counter-cyclical job opportunities in addition to or away from older businesses that may lack the flexibility to adapt to adverse demand conditions (Simmie and Martin, 2010; Martin, 2012). In the empirical analysis, we focus on the role of technological variety, coherence, high-tech activities and entrepreneurship. In testing their relative contribution to regional resilience, we take into account the effect of the region's absorptive capacity, employment specialisation and agglomeration economies. Adapting Cohen and Levinthal's (1989) approach to a regional context, we refer to absorptive capacity as the region's ability to identify, assimilate and exploit knowledge from the environment. We also include a control for the relative share of employment in different occupations. Finally, we account for agglomeration effects because the existence of urbanisation economies can provide stronger infrastructures for the production, absorption, and exchange of knowledge (Frenken et al. 2007) and this can have a significant impact on resilience (Capello, 2015; Lee, 2014).

3. Data and Variables

3.1 Dataset

We combine information on the employment and industrial structure of UK NUTS III regions with information on patent records. The data sources are respectively the Nomis portal of the UK Office of National Statistics and the European Patent Office's PATSTAT database. We consider patent applications submitted to EPO by inventors resident in the different NUTS III UK regions.[3] Following a well-established tradition, we use information contained in patent applications to characterise regional economies since applications as the outcome of R&D investments are good indicators of technological capabilities (Jaffe and Trajtenberg, 2000). Patents are grouped into 8 technological classes and 121 sub-classes according to the International Patent Classification (IPC), and the analysis uses 3-digits technology codes. We also draw from PATSTAT data on the number of patents in high-tech sectors.

The econometric analysis is carried out with data on 134 UK NUTS III regions observed over the 2004-2012 period. This spatial unit of analysis captures at a satisfactory level of dis-aggregation the dynamics of local economies (including production activities and labour markets) as theorised in the new economic geography literature as well as research on agglomeration economies (Frenken et al., 2007). The span of the time series is also appropriate because it contains the 2008 financial crisis as a major exogenous shock. The final dataset is a balanced panel of 1,206 observations, with data merged on the basis of NUTS III regional code and year.

3.2 Variables and Measures

Dependent Variable

In our empirical analysis the dependent variable is the degree of resilience displayed by the UK NUTS III regions throughout the financial downturn that started in 2008. Martin and Simmie (2010) employ the evolution of the regional employment rate as a proxy for

[3] In the PATSTT database, patent applications are counted according to the year in which they are filed. Moreover, they are assigned to a country/region on the basis of the inventor's place of residence, using fractional counting if there are multiple inventors for a single patent. They can be presented at a national or regional level; in the latter case, the data are aggregated by linking postcodes and/or place names to NUTS level 2 and 3 regions.

resilience. They argue that it is the most appropriate measure because 'the proportionate decline in employment during a recessionary downturn tends to be significantly greater than that in output. In this respect, the issue of regional resilience assumes particular significance in relation to how regional and local labour markets are affected by and recover from major recessionary shocks' (Martin et al., 2012: p.110). For these reasons evaluating differential employment effects is an efficient empirical strategy to assess the impact of exogenous shocks on regional economies (Di Caro, 2015; Fingleton, 2012; Lee, 2014). Holm and Østergaard (2015) also use the growth rate of ICT employment in each region to investigate the resilience of the Danish information and communication technology (ICT) sector to the burst of the dot.com bubble of the late 90s.

Following the prior art, the key variable of our model is the yearly growth rate of Employment ($gEmp_{i,t}$) in each NUTS III i at time t.

The variable is calculated over the period 2004-2012 as follow:

$$gEmp_{i,t} = \frac{Emp_{i,t} - Emp_{i,t-1}}{Emp_{i,t-1}}$$

Independent Variables

We want to investigate the effect of different technological profiles on the capacity of regional economies to be resilient to exogenous shocks. More precisely, we are interested in the impact of different degrees *and* types of technological diversification on resilience. Therefore, we introduce in the estimation different indicators of variety: Regional Entropy, Unrelated and Related variety.

Theil originally introduced the Information Entropy Index (H) to economic analysis in 1967 in order to measure the degree of disorder or randomness of a system (Theil, 1967). In its earliest applications, it was used to analyse how different economic activities were distributed between sectors, firms or regions (Attaran, 1985; Frenken et al., 2007; Boschma and Iammarino, 2009). We use this index as a first measure of the degree of regional technological diversification.

One of the main advantages of this specific measure is that entropy can be decomposed at each technology digit level (Theil, 1972; Jacquemin and Berry, 1979). We compute the index by using patent data at the three-digit level available for each UK NUTS III units. Thus, related variety is measured at a lower level of aggregation (3-digit class within a 1-digit section) than unrelated variety (across 1-digit section). The first measure captures the average degree of disorder or variety within the subsets, while the second captures the degree of randomness between the higher-order sections. Following Frenken et al. (2007) we assume that all the events E_i $(i = 1, \dots., n)$ can be aggregated into a few sets of events $S_1, \dots \dots, S_G$ in such a way that each event falls exclusively within a single set S_g where g = 1,…,G. Each of the 121 patent classes can be grouped into one of 8 technological sections of the IPC standard classification. The probability of the event $E_i$in S_g occurs is obtained by summation:

$$P_g = \sum_{i \in S_g} p_i$$

Therefore, the between-group entropy or Unrelated Variety (UV) measured between patent sections is calculated as follow:

$$UV = \sum_{i \in S_g} P_g \, log_2 \left(\frac{1}{P_g} \right)$$

The entropy decomposition theorem specifies that the relation between Unrelated Variety and the regional total Information Entropy can be defined as follow:

$$H = UV + \sum_{g=1}^{G} P_g \, H_g$$

where Related Variety (RV) or within group entropy represents the second part of the equation

$$RV = \sum_{g=1}^{G} P_g \, H_g$$

$$H_g = \sum_{i \in S_g} \frac{p_i}{P_g} log_2 \left(\frac{1}{\frac{p_i}{P_g}} \right)$$

The total entropy measure is heavily influenced by the relative dynamics of related and unrelated variety. If the effect of unrelated technological variety is dominant, the effects of total entropy on resilience, measured as yearly variation in the employment rate, is expected to be negative. The index has a positive effect on regional adaptability if related technological variety plays a predominant role because it fosters spillovers that feed more efficiently into processes of knowledge recombination (Boschma, 2005; Nooteboom et al., 2007; Plum and Hassink, 2014). Conversely, regions with a predominant effect of unrelated variety experience fewer inter-industries externalities because cognitive distances between technology domains are more pronounced and therefore more difficult to manage. One drawback of the Information Entropy Index (H) is that it is highly dependent on the IPC (International Patent Classification) hierarchical classification and may fail to capture broader notions of technological relatedness or epistemic proximity between different groups of patents.

We then calculate a Regional Technological Coherence (C) index as the average epistemic relatedness of any technology randomly chosen within a region with respect to any other technology (Nesta and Saviotti, 2005 and 2006; Nesta, 2008). The index allows us to evaluate the extent of regional diversification while taking into account the volume of patenting activities in different classes weighted by their degree of technological proximity.

The value of C is calculated as follow. Firstly, we compute the Coherence Index introduced by Teece et al. (1994). Our universe is made of 134 NUTS III regions each patenting in the period 2004-2012 in two or three technological fields (IPC classification). If region r in the year t is active in technological field i $G_{ik} = 1$, otherwise $G_{ik} = 0$. Therefore, the total number of regions active in technology i *is equal to* $R_i = \sum_i G_i$. In the same fashion the number of regions patenting both in the fields i and j is computed as follow: $O_{ij} = \sum_t G_i G_j$. By applying this formula to all possible pairs of technological fields we obtain a square (8 X 8) symmetrical matrix Ω, in which the generic cell O_{ij} records the number of regions that each year (from 2004 to 2012) were active in both technological fields i and j. Following Teece et al. (1994), the Coherence Index (τ_{ij}) is computed as a 'test of randomness' that compares the observed value of O_{ij} with the value that would be expected under the hypothesis that technological diversification is random:

$$\tau_{ij} = \frac{O_{ij} - \mu_{ij}}{\sigma_{ij}}$$

where μ_{ij} is the media of the counterfactual random sample X_{ij}

$$\mu_{ij} = E(X_{ij}) = \frac{R_i R_J}{T}$$

and σ_{ij} is its variance

$$\sigma_{ij}^2 = \mu_{ij} \left(1 - \frac{R_i}{T}\right)\left(\frac{T - R_J}{T - 1}\right)$$

On this basis we proceed to calculate the Weighted Average Relatedness WAR_{jit} of technology *j* (in region *i* at time *t*) with respect to all other technologies present within the region.

$$WAR_{jit} = \frac{\sum_{m \neq j} \tau_{jm} P_{mit}}{\sum_{m \neq i} P_{mit}}$$

WAR_{jit} is defined as the degree to which technology j is related to all other technologies $m \neq j$ within the region i (at time t), weighted by the number of patent P_{mit}. Finally, the Regional Technological Coherence (C) of region i at time t is defined as the weighted average of the WAR_{jit}:

$$C_{it} = \sum_{J \neq m} WAR_{jit} \frac{P_{jit}}{\sum_j P_{jit}}$$

where $\sum_j P_{jit}$ is the total number of patents within the region i (NUTS III).

This measure captures the degree to which the different classes of patents making up the technological knowledge base of a region are complementary to one another. This makes the coherence index particularly appropriate for our research objectives. We expect that this index will be positively related to regional resilience since, as we explained earlier, we conjecture that technological proximity plays a key role in prompting recombinant growth processes within regions.

We include among the focal determinants of resilience the ability of a region to innovate in newer technological fields and entrepreneurship. These two variables are defined as follow. Employing the data on the number of patents filed in high-tech sectors for each NUTS III region we construct the variable Patents in high tech sector (HT_pat) to capture the extent of innovation in technologies associated with the strongest growth opportunities. The definition of high-technology patents uses the specific subclasses of the International Patent Classification (IPC) identified in the trilateral statistical report of the EPO, the Japanese Patent Office (JPO) and the United States Patent and Trademark Office (USPTO).[4] They are: aviation, communication technology, computer and automated business equipment, lasers, microorganism and genetic engineering and semiconductors.

[4] Source: Eurostat, High-tech patent applications to the European patent office (EPO) by priority year, http://ec.europa.eu/eurostat/web/products-datasets/-/tsc00010.

The variable Entry measures the rate at which new firms appear in the local economy. New firm formation has been extensively used in the literature on the relationship between entrepreneurship and regional growth (Audretsch and Fritsch, 2002; Fritsch and Mueller, 2004; Acs and Armington, 2004; Baptista et al. 2008; Doran et al. 2016, among others). We use it to identify the effect of entrepreneurship on resilience and calculate it as the year-on-year growth rate of the number of firms active in each NUTS III units. The expectation derived from theory is that regions endowed with more new firms are better prepared to face unforeseen shocks and display resilience.

We include controls for other regional characteristics, such as education levels of the workforce and population density. We use the share of employees with the lowest level of education for each NUTS III region (that is the number of workers with National Vocational Qualifications – NVQ) to measure weak absorptive capacity. [5] We expect that a larger share of lower education levels will negatively influence regional resilience. Moreover, to account for patterns of specialisation in the regional employment we compute an index equal to the ratio between the share of employment in elementary occupations and the share of science and technology-related jobs (LT_jobs). Regions with a comparatively weaker specialisation in high-tech jobs are less likely to engage in those cutting-edge innovation processes that are likely to make the region more resilient to downturns. Population density (Density) is finally added as a proxy for the agglomeration patterns of UK NUTS III micro-regions as in Frenken et al. (2007)'s study.

The dummy variable Crisis enters the econometric analysis to assess the role of the 'Great Recession' and more specifically to test how the structure of local technological knowledge mediates the effect of the downturn. When we look at the main trend in

[5] Using inverse measures reduces the risk of multicollinearity in the estimation while capturing the relative effects of high and low absorptive capacities of regional labour markets.

employment (Figure 1) for the period 2004-2012 it is evident that the financial crisis of 2008 began to affect the British job market in 2009. The year 2012 marked a reversal of the recessionary trend but did not bring employment back on a par with the pre-crisis period.[6] The variable Crisis is defined as 0 until and including the year 2008 and 1 afterwards.

>>>INSERT FIGURE 1 ABOUT HERE<<<

3.3 Descriptive Statistics

Table 1 provides the descriptive statistics for the whole dataset and Table 2 shows the correlation matrix. Generally, correlation levels are low. We notice that the only variables significantly correlated are Information Entropy (H), Related Variety (RV) and Unrelated Variety (UV). This is due to the calculation of the indices: as we have explained in the previous section, the Entropy measure results from the sum of the variables RV and UV, and we need to keep this in mind when we estimate the model.

>>>INSERT TABLE 1 ABOUT HERE<<<

>>>INSERT TABLE 2 ABOUT HERE<<<

To gain a first insight into the cross-regional differences in our sample we examine the geographical distribution of key variables across the 134 NUTS III UK micro regions. As we can see from Figure 2, the growth rate of employment over the period 2004 to 2012 is on average largely negative; just 49 out of 134 English micro regions registered a moderately

[6] We anticipate that robustness checks performed on our econometric model by excluding the year 2012 from the sample do not change the results.

positive change in their employment performance. Furthermore, the map in Figure 2 highlights that resilience over the whole period is unevenly distributed across UK regions.

>>>INSERT FIGURE 2 ABOUT HERE<<<

This unevenness can be detected as clearly when we split the observations between the pre-crisis and crisis periods. Inter-regional differences will be analysed in detail in the econometric exercise that follows (in Section 4), but we can already see in Figure 3 how regions with positive growth are much more numerous in the first relative to the second period, that persistent growth across periods is rare, and that the Figure with data on the crisis period (on the right-hand side) presents more areas of markedly negative growth among the Northern regions. Figures 4 and 5 illustrate technological coherence and entropy, respectively, for the pre-crisis and the crisis period. They provide not only clear indications of variability across regions and through time, but also of significant differences in the technological characteristics captured by our indices of variety.

>>>INSERT FIGURE 3 ABOUT HERE<<<

>>>INSERT FIGURE 4 ABOUT HERE<<<

>>>INSERT FIGURE 5 ABOUT HERE<<<

4. Econometric Analysis and Findings

To investigate the effects of different technological profiles on resilience, and to evaluate at the same time the ‘within’ and ‘between’ variation of the micro-regions, we use a pooled OLS model. In order to account for unobserved heterogeneity and for potential sensitivity to outliers, we also ran fixed effect models and robust estimations (included in Table 6 and Table 7). These fully confirm the results.

In the estimations, we adopt a stepwise approach: first of all, we estimate a model designed to explain the regional variation in employment within regions and across regions; secondly, in order to evaluate how the regional technological structure mediates the effect of the recession, we interact the dummy variable for the crisis period (defined as 0 until and including the year 2008, 1 afterwards) with the focal determinants of resilience.

The baseline model we use takes the form:

$$gEmp_{i,t} = \beta_0 + \beta_2 C_{i,t-1} + \beta_3 entropy_{i,t-1} + \beta_4 NVQ_{i,t-1} + \beta_5 HT\_pat_{i,t-2} + \beta_6 LT\_jobs_{i,t-1} + \beta_7 density_{i,t-1} + \beta_8 entry_{i.t-1} + \beta_9 crisis_{i,t} + u_{i,t} \quad \text{(Model 1)}$$

where $\mathrm{gEmp}_{i,t}$ represents the variation in the employment rate of region i from year t to year $\mathrm{t}-1$. All explanatory variables are lagged by one period, with the exception of the variable $\mathrm{pathtech}_{i,t}$: this is lagged by an additional year to reflect more accurately the lags of the patenting process (Griliches and Pakes, 1984).

As we already noticed in commenting on Table 2, the variables Entropy, RV and UV are highly correlated. Therefore, they enter the estimations separately and in a stepwise manner.

In order to evaluate how the regional technological structure moderates the effect of the financial crisis – and therefore to test the determinants of regional resilience to this shock – we then interact key explanatory variables (C, Entropy, RV, UV, HT_pat and Entry) with the crisis period dummy. Thus, this second model takes the form

$$gEmp_{i,t} = \beta_0 + \beta_2 C_{i,t-1} + \beta_3 entropy_{i,t-1} + \beta_4 NVQ_{i,t-1} + \beta_5 HT\_pat_{i,t-2} + \beta_6 LT\_jobs_{i,t-1} + \beta_7 density_{i,t-1} + \beta_8 entry_{i.t-1} + \beta_9 crisis_{i,t} + \beta_{10} crisis_{i,t} C_{i,t-1} + \beta_{11} crisis_{i,t} entropy_{i,t-1} + +\beta_{12} crisis_{i,t} HT\_pat_{\ i,t-2} + \beta_{13} crisis_{i,t}\ entry_{i,t-1} + u_{i,t}$$

(Model 2)

Table 3 reports the results of the estimations that alternatively include Entropy (Column 1), RV (Column 2) and UV (Column 3). Table 4, instead, reports results with the coefficients on standardised variables, which allow us to directly compare the effects of the explanatory variables not only in terms of sign but also of magnitude.

As far as the variables Entropy, RV and UV are concerned, the results of the baseline estimations reported in Table 3 and 4 show that their coefficient is insignificant. Thus, in contrast with evidence found in previous literature all the measures of diversification appear to have no effect on employment growth. Regional Technological Coherence (C) has instead a positive and significant coefficient in all estimations. This result suggests that diversifying in technological coherent patent classes is a fundamental determinant of employment creation. They also show that, in line with previous literature, that the effect of low skills employment (NVQ) is negative and statistically significant in all the estimations, which means that greater shares of low skilled employees make the regional economy less able to improve their occupational profile.

Interestingly, new firm formation (the variable Entry) has insignificant (negative) coefficients both in Table 3 and 4. Finally, these results indicate that, as expected, the recession (Crisis) had an important negative influence on job growth.

The results of the interacted model highlight that all measures of diversification show a negative but insignificant coefficient (Table 3). Therefore, we find that the portfolio diversification is not affecting resilience. C and HT_pat exhibit instead positive and significant coefficients in all estimations, demonstrating that the sources of resilience are to be found in the technological coherence of the regional economy and in its orientation towards innovation in sectors associated with the strongest technological opportunities.

Moreover, the evidence presented in Table 3 indicates that the variable Entry also has a non-significant effect on resilience. Contrary to our expectations, the results suggest that new firms per se do not have any effect on the resilience of regions.

Table 4 reports results obtained with standardised coefficients. These confirm that Regional Technological Coherence (C) and patent intensity in high-tech have indeed an important positive impact on resilience and play a crucial role in fostering a regional economy's adaptability to shocks.

>>>INSERT TABLE 3 ABOUT HERE<<<

>>>INSERT TABLE 4 ABOUT HERE<<<

4.1 Robustness checks

We have identified Regional Technological Coherence (C) and patent intensity in high-tech (HT_pat) as main drivers of resilience throughout the financial crisis of 2008. We have also shown that technological variety does not influence resilience.

In order to test the robustness of these results we perform the same estimations by using an alternative measure of variety. We include in both regressions a new measure of diversification ($Div_{i,t}$) which is equal to the fractionalisation index proposed by Alesina et al. (2003):

$$Div_{\ i,t} = 1 - Herfindahl_{i,t}$$

A low index value means that patents within the NUTS III region are concentrated in a few patent classes. Conversely, a higher value indicates greater variety in the distribution of regional patents among different classes. The baseline estimation results presented by Table 5 indicate that our results are robust. The Regional Coherence indicator (C) remains positively related to employment growth, while we again find evidence of negative effects for the crisis and NVQ variables. This shows that changing the indicator for diversification does not substantially change the results, which still indicate a non-significant effect on regional employment variation.

The results of the interacted model in Table 5 also validate our conjectures and previous results. During the crisis period, Regional Coherence (C) and the patent intensity in high tech (HT_pat) are confirmed to be important drivers of resilience.

>>>INSERT TABLE 5 ABOUT HERE<<<

To further test the robustness of our modelling strategy and in order to account for unobserved heterogeneity and potential sensitivity to outliers, we also ran fixed effect models and robust estimations. The results are presented in Table 6 and Table 7 and fully confirm the findings.

5. Conclusion

In this study we have explored the factors affecting the resilience of UK NUTS III regional economies to the Great Recession. The paper offers an original contribution by focusing on the role played by the different regional technological profiles on the degree of adaptability to external shocks.

The descriptive statistics revealed that the capacity to react to the crisis period was very uneven across UK regions and we conjectured that a fundamental reason had to reside in the technological heterogeneity of local innovation systems. We set out to explore the determinants of regional adaptive resilience through panel analyses of the effect of the 2008 recession in the UK. The results suggest that the degree of Regional Technological Coherence and patenting in high-tech are key drivers of the regions' ability to adapt to the shock.

We also demonstrate that all other measures of regional variety have no significant effect on resilience. This is arguably due to the fact that the process of knowledge recombination is more effective when there are strong functional ties between technologies rather than in the presence of technological variety per se. A high degree of technological variety within the region may indeed correspond to greater cognitive distance between economic agents, hindering recombinant growth processes and preventing the emergence of innovative solutions to the immediate threat of decline.

It can be argued that in the short-to-medium term it is easier and less costly to utilise related knowledge inputs because of the less significant transaction costs involved in linking cognitively closer areas of expertise. This might be especially true at times of resource constraints and greater uncertainty about returns from untested combinations of knowledge inputs. Further research might shed light on the long-term patterns of resilience, for example by testing whether sustained recovery from employment losses due to the recession might indeed be related to greater technological diversity rather than coherence. Only the addition of more year-observations to our panel will help us address this important question.

From a policy viewpoint, this study draws attention to the role of a coherent technological structure and to the strategic importance of innovative activities in growing sectors in mitigating the negative effects of the crisis. Thus, policies that aim to foster regional resilience should start by a careful assessment of the technological composition of the local economic landscape. The identification of specific areas of expertise is important to devise the most appropriate incentive schemes and to design innovation policies directed towards the generation of coherent new knowledge with a strong component of innovation at the technological frontier.

We also found that new firms did not play a significant role in enhancing adaptive resilience. This indicates that in the process of regional development the innovativeness of the productive system is more important than its capacity to generate new ventures per se. It is possible that entrepreneurship may have an effect on the regional economies' adaptability if the creation of the new companies is embedded in a strong technological base. However, when we explicitly tested for the combined effect (a three-way interaction) of entry, knowledge-intensity, and the crisis dummy, we did not obtain statistically significant results.[7] There might be different explanations for this. The first is that it might take longer for entrepreneurship to have a positive impact on jobs relative to other variables and that its effect will be observed at a later stage of the recovery process. Recent empirical evidence suggests that entrepreneurship may indeed play a fundamental role in enhancing regional growth during recovery phases rather than crisis period (Kitsos and Bishop, 2016).

The second explanation is in line with the view that only a minority of firms are responsible for the creation of new jobs. These are relatively rare, and while the generation of any such firm will benefit the regional economy, the addition of an 'average' firm will have no positive net effect because the 'average' firm on a fat-tailed distribution of growth rates is not innovative (Shane, 2009; Coad and Nightingale, 2014). Complementary firm-level studies in a comparative international setting will be ideally placed to dig deeper into this

[7] These results are not included in the paper but are available upon request from the authors [Table 8 in the Appendix for the referee].

more specific question. The modelling of knowledge interdependencies might prove important also in this stream of research and could extend further the analysis of resilience in a multi-level (firm-region) framework.

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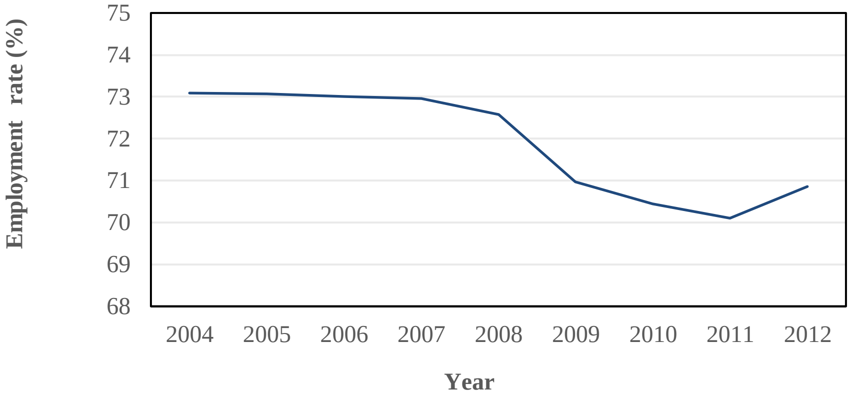
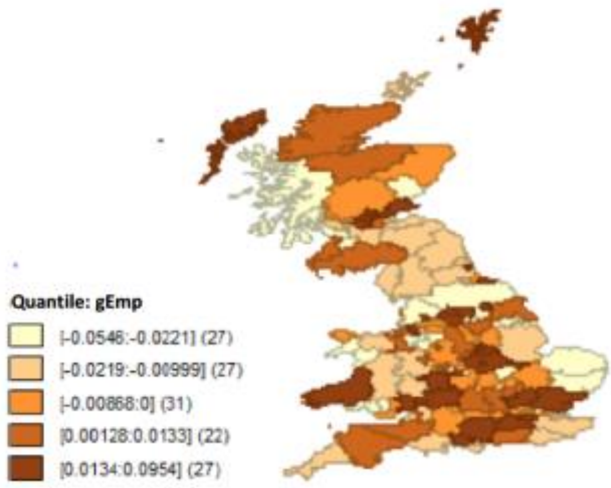
Figure 1 - Evolution of UK Employment 2004-2012



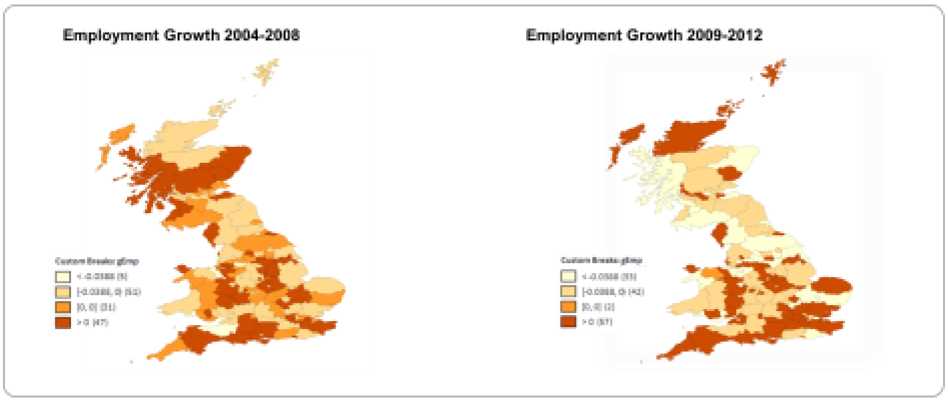
Source: NOMIS-PATSTAT, own calculations

Figure 2 - Employment growth across UK regions 2004-2012



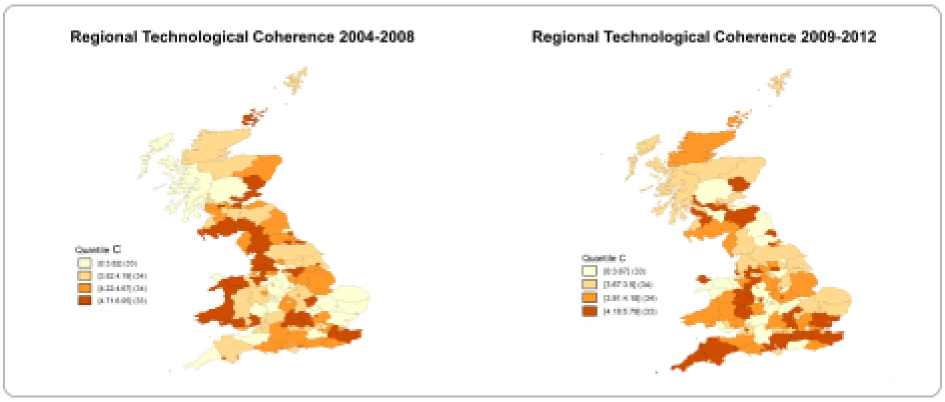
Source: NOMIS-PATSTAT, own calculations

Figure 3 - Employment growth across UK regions pre-crisis years and crisis years (period averages)



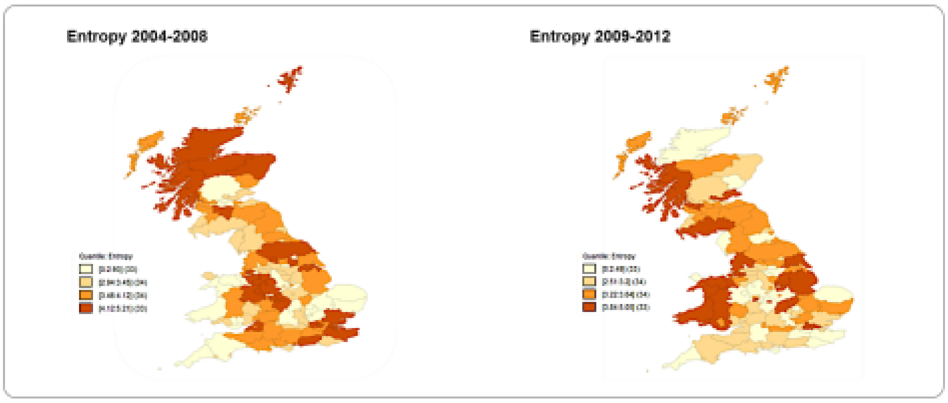
Source: NOMIS-PATSTAT, own calculations

Figure 4 - Regional technological coherence across UK regions pre-crisis years and crisis years (period averages)



Source: NOMIS-PATSTAT, own calculations

Figure 5 - Entropy across UK regions pre-crisis years and crisis years (period averages)



Source: NOMIS-PATSTAT, own calculations

Table 1 - Descriptive statistics (whole sample)

	Obs	Mean	Std. Dev.	Min	Max
gEmp	1072	-0,004	0,03	-0,11	0,12
C	1164	3,95	0,68	0,00	8,59
Entropy	1206	3,16	1,18	0,00	5,21
RV	1206	1,14	0,62	0,00	2,59
UV	1206	2,02	0,67	0,00	2,92
NVQ	1204	7,93	3,57	0,70	24,00
HT_pat	982	10,01	20,20	0,00	180,48
LT_jobs	1206	1,47	0,21	0.207	10,62
Density	1206	1245,50	1694,92	7,10	10391
Entry	1072	0,14	0,19	-0,85	5,96
Crisis	1206	0,44	0,50	0,00	1,00

Table 2 - Correlation Matrix

	gEmp	C	Entropy	RV	UV	NVQ	HT_pat	LT_jobs	Density	Entry	Crisis
gEmp	1										
C	0.0897	1									
Entropy	-0.0714	-0.0250	1								
RV	-0.0436	-0.0457	0.9061	1							
UV	-0.0860	0.0014	0.8997	0.6306	1						
NVQ	-0.0585	0.0273	-0.0969	-0.1209	-0.0530	1					
HT_pat	0.0075	-0.0911	0.2807	0.3358	0.1684	-0.2136	1				
LT_jobs	0.0073	-0.0029	-0.0494	-0.0268	-0.0630	0.0711	-0.0886	1			
Density	-0.0000	-0.0463	0.0246	0.0136	0.0312	0.0871	0.1714	-0.0126	1		
Entry	0.0131	0.0467	0.0182	-0.0039	0.0374	0.0332	-0.0062	-0.0108	-0.0721	1	
Crisis	-0.0719	-0.0223	-0.1760	-0.1519	-0.1661	0.0320	0.0097	-0.0508	0.0182	0,0182	1

Table 3 - Results of the pooled OLS estimations

Dep var: gEmp		**Baseline**			**Interacted**	
	(1)	(2)	(3)	(1)	(2)	(3)
Entropy	-0.000190			0.00231		
	(0.00264)			(0.00270)		
RV		-0.00356			-0.000836	
		(0.00373)	0.00395		(0.00397)	
UV			(0.00416)			0.00863
						(0.00449)
C	0.0250**	0.0255**	0.0250**	0.00144	0.00474	-0.000419
	(0.00891)	(0.00891)	(0.00890)	(0.00834)	(0.00807)	(0.00831)
NVQ	-0.00203**	-0.00200**	-0.00203**	0.000102	0.000119	0.0000182
	(0.000760)	(0.000760)	(0.000759)	(0.000746)	(0.000746)	(0.000740)
HT_pat	0.000647	0.000646	0.000722	-0.000410	-0.000306	-0.000317
	(0.00152)	(0.00151)	(0.00152)	(0.00147)	(0.00147)	(0.00147)
LT_jobs	-0.000488	-0.000475	-0.000503	-0.000542	-0.000467	-0.000579
	(0.000640)	(0.000639)	(0.000639)	(0.000613)	(0.000611)	(0.000611)
Density	0.0000172	0.0000170	0.0000169	-0.0000172	-0.0000132	-0.0000232
	(0.0000212)	(0.0000212)	(0.0000212)	(0.0000147)	(0.0000141)	(0.0000147)
Entry	-0.00572	-0.00575	-0.00608	-0.00385	-0.00380	-0.00423
	(0.00463)	(0.00462)	(0.00463)	(0.00445)	(0.00445)	(0.00445)
Crisis	-0.00612*	-0.00615*	-0.00606*	-0.0201***	-0.0199***	-0.0205***
	(0.00264)	(0.00264)	(0.00264)	(0.00305)	(0.00304)	(0.00305)
Entropy*crisis				-0.00385		
				(0.00241)		
RV*crisis					-0.00460	
					(0.00397)	
UV*crisis						-0.00818
						(0.00460)
C*crisis				0.0265***	0.0206***	0.0303***
				(0.00681)	(0.00452)	(0.00810)
HT_pat*crisis				0.00299*	0.00277*	0.00289*
				(0.00132)	(0.00133)	(0.00129)
Entry*crisis				-0.0441	-0.0462	-0.0413
				(0.0318)	(0.0318)	(0.0318)
Regional dummies	YES	YES	YES	YES	YES	YES
Constant	-0.0408	-0.0371	-0.0493			
	(0.0286)	(0.0277)	(0.0285)			
R-sq	0.12	0.12	0.12	0.22	0.22	0.22
Observations	747	747	747	747	747	747
Nr of regions	131	131	131	131	131	131

Estimated intercept and slope coefficients for each regressor with robust standard errors in parenteses. Asterisks denote significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 4 - Results of the pooled OLS estimations with standardised coefficients

Dep var: gEmp	**Baseline**			**Interacted**		
	(1)	(2)	(3)	(1)	(2)	(3)
Entropy	-0.000223			0.00323		
	(0.00310)			(0.00331)		
RV		-0.00219			-0.000426	
		(0.00230)			(0.00246)	
UV			0.00265			0.00674*
			(0.00279)			(0.00315)
C	0.00380**	0.00387**	0.00381**	0.000538	0.000900	0.000488
	(0.00135)	(0.00135)	(0.00135)	(0.00138)	(0.00136)	(0.00137)
NVQ	-0.00786**	-0.00776**	-0.00786**	0.000866	0.000664	0.000944
	(0.00294)	(0.00294)	(0.00294)	(0.00300)	(0.00299)	(0.00298)
HT_pat	0.000926	0.000926	0.00103	-0.000496	-0.000400	-0.000292
	(0.00217)	(0.00217)	(0.00217)	(0.00212)	(0.00212)	(0.00210)
LT_jobs	-0.000742	-0.000721	-0.000764	-0.000786	-0.000688	-0.000818
	(0.000971)	(0.000970)	(0.000970)	(0.000932)	(0.000931)	(0.000929)
Density	0.0291	0.0288	0.0286	-0.0153	-0.0168	-0.0149
	(0.0359)	(0.0359)	(0.0359)	(0.0300)	(0.0300)	(0.0299)
Entry	-0.00107	-0.00107	-0.00113	-0.000739	-0.000715	-0.000836
	(0.000861)	(0.000859)	(0.000862)	(0.000830)	(0.000829)	(0.000830)
Crisis	-0.00612*	-0.00615*	-0.00606*	-0.0198***	-0.0196***	-0.0200***
	(0.00264)	(0.00264)	(0.00264)	(0.00303)	(0.00303)	(0.00303)
Entropy*crisis				-0.00657		
				(0.00405)		
RV*crisis					-0.00304	
					(0.00263)	
UV*crisis						-0.00934
						(0.00493)
C*crisis				0.0182***	0.0140***	0.0212***
				(0.00465)	(0.00308)	(0.00555)
HT_pat*crisis				0.00323*	0.00305*	0.00303*
				(0.00149)	(0.00150)	(0.00145)
Entry*crisis				-0.00124	-0.00129	-0.00118
				(0.000881)	(0.000882)	(0.000880)
Regional dummies	YES	YES	YES	YES	YES	YES
Constant	-0.00381	-0.00296	-0.00397			
	(0.0128)	(0.0128)	(0.0128)			
R-sq	0.12	0.12	0.12	0.22	0.22	0.22
Observations	747	747	747	751	751	751
Nr of regions	131	131	131	131	131	131

Estimated intercept and slope coefficients for each regressor with robust standard errors in parentheses. Asterisks denote significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 5 - Results of the pooled OLS estimations with an alternative measure of variety

Dep var: gEmp	Baseline	Interacted
	(1)	(1)
Div	-0.0175	-0.0224
	(0.00925)	(0.0120)
C	0.0250**	0.00844
	(0.00888)	(0.00891)
NVQ	-0.00187*	0.000105
	(0.000766)	(0.000777)
HT_pat	0.000721	-0.000156
	(0.00151)	(0.00148)
LT_jobs	-0.000538	-0.000513
	(0.000639)	(0.000614)
Density	0.0000170	-0.0925
	(0.0000212)	(0.105)
Entry	-0.0116	-0.00625
	(0.00880)	(0.00913)
Crisis	-0.00599*	-0.0185***
	(0.00265)	(0.00334)
Div*crisis	-0.0318	0.00974
	(0.0278)	(0.0138)
C*crisis		0.0132*
		(0.00545)
HT_pat*crisis		0.00273*
		(0.00136)
Entry*crisis		-0.0228
		(0.0235)
Regional dummies	YES	YES
Constant	-0.0318	
	(0.0278)	
R-sq	0.12	0.22
Observation	744	744
Nr of regions	131	131

Estimated intercept and slope coefficients for each regressor with robust standard errors in parentheses. Asterisks denote significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 6 - Results of Fixed effects estimation

Dep var: gEmp		**Baseline**			**Interacted**	
	(1)	(2)	(3)	(1)	(2)	(3)
Entropy	-0.000190			0.00274		
	(0.00264)			(0.00281)		
RV		-0.00356			-0.000700	
		(0.00373)	0.00395		(0.00401)	
UV			(0.00416)			0.0100
						(0.00470)
C	0.0250**	0.0255**	0.0250**	0.00352	0.00583	0.00318
	(0.00891)	(0.00891)	(0.00890)	(0.00913)	(0.00902)	(0.00907)
NVQ	-0.00203**	-0.00200**	-0.00203**	0.000225	0.000178	0.000245
	(0.000760)	(0.000760)	(0.000759)	(0.000778)	(0.000778)	(0.000775)
HT_pat	0.000647	0.000646	0.000722	-0.000345	-0.000274	-0.000203
	(0.00152)	(0.00151)	(0.00152)	(0.00148)	(0.00148)	(0.00147)
LT_jobs	-0.000488	-0.000475	-0.000503	-0.000518	-0.000453	-0.000539
	(0.000640)	(0.000639)	(0.000639)	(0.000614)	(0.000613)	(0.000612)
Density	0.0000172	0.0000170	0.0000169	-	-	-
				0.00000883	0.00000902	0.00000856
	(0.0000212)	(0.0000212)	(0.0000212)	(0.0000209)	(0.0000210)	(0.0000209)
Entry	-0.00572	-0.00575	-0.00608	-0.00397	-0.00384	-0.00449
	(0.00463)	(0.00462)	(0.00463)	(0.00446)	(0.00446)	(0.00446)
Crisis	-0.00612*	-0.00615*	-0.00606*	-0.0198***	-0.0197***	-0.0200***
	(0.00264)	(0.00264)	(0.00264)	(0.00310)	(0.00310)	(0.00310)
Entropy*crisis				-0.00391		
				(0.00241)		
RV*crisis					-0.00458	
					(0.00398)	
UV*crisis						-0.00870
						(0.00463)
C*crisis				0.0266***	0.0206***	0.0310***
				(0.00682)	(0.00453)	(0.00814)
HT_pat*crisis				0.00288*	0.00271*	0.00271*
				(0.00134)	(0.00135)	(0.00131)
Entry*crisis				-0.0449	-0.0466	-0.0426
				(0.0319)	(0.0319)	(0.0318)
Regional dummies	YES	YES	YES	YES	YES	YES
Constant	-0.0388	-0.0353	-0.0482	-0.00707	0.00105	-0.0200
	(0.0317)	(0.0307)	(0.0318)	(0.0311)	(0.0302)	(0.0313)
R-sq	0.09	0.08	0.08	0.13	0.13	0.14
Observations	747	747	747	747	747	747
Nr of regions	131	131	131	131	131	131

Estimated intercept and slope coefficients for each regressor with robust standard errors in parentheses. Asterisks denote significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 7 - Results of the robust pooled OLS estimations

Dep var: gEmp	Baseline			Interacted		
	(1)	(2)	(3)	(1)	(2)	(3)
Entropy	-0.000506			0.00313		
	(0.00275)			(0.00292)		
RV		-0.00505			-0.00204	
		(0.00389)	0.00475		(0.00414)	
UV			(0.00435)			0.0116
						(0.00484)
C	0.0294**	0.0302**	0.0296**	0.00871	0.0108	0.00894
	(0.00930)	(0.00930)	(0.00931)	(0.00946)	(0.00933)	(0.00935)
NVQ	-0.00180*	-0.00179*	-0.00180*	0.000505	0.000401	0.000548
	(0.000794)	(0.000792)	(0.000794)	(0.000807)	(0.000804)	(0.000798)
HT_pat	0.000462	0.000517	0.000520	-0.000748	-0.000566	-0.000440
	(0.00158)	(0.00158)	(0.00159)	(0.00153)	(0.00153)	(0.00152)
LT_jobs	-0.000349	-0.000333	-0.000401	-0.000283	-0.000253	-0.000275
	(0.000668)	(0.000667)	(0.000669)	(0.000637)	(0.000634)	(0.000631)
Density	0.0000136	0.0000140	0.0000129	-0.00000869	-0.00000816	-0.00000923
	(0.0000221)	(0.0000221)	(0.0000222)	(0.0000217)	(0.0000217)	(0.0000215)
Entry	-0.00523	-0.00527	-0.00566	-0.00417	-0.00395	-0.00479
	(0.00483)	(0.00482)	(0.00485)	(0.00463)	(0.00461)	(0.00460)
Crisis	-0.00539*	-0.00546*	-0.00541*	-0.0196***	-0.0194***	-0.0200***
	(0.00276)	(0.00275)	(0.00276)	(0.00322)	(0.00321)	(0.00319)
Entropy*crisis				-0.00354		
				(0.00250)		
RV*crisis					-0.00501	
					(0.00411)	
UV*crisis						-0.00660
						(0.00477)
C*crisis				0.0258***	0.0209***	0.0279***
				(0.00707)	(0.00468)	(0.00839)
HT_pat*crisis				0.00302*	0.00299*	0.00276*
				(0.00139)	(0.00139)	(0.00134)
Entry*crisis				-0.0378	-0.0400	-0.0358
				(0.0330)	(0.0330)	(0.0328)
Regional dummies	YES	YES	YES	YES	YES	YES
Constant	-0.0459	-0.0422	-0.0568	-0.0270	-0.0156	-0.0411
	(0.0299)	(0.0289)	(0.0299)	(0.0289)	(0.0279)	(0.0288)
R-sq	0.12	0.12	0.12	0.22	0.22	0.22
Observations	747	747	747	747	747	747
Nr of regions	131	131	131	131	131	131

Estimated intercept and slope coefficients for each regressor with robust standard errors in parentheses. Asterisks denote significance: * p<0.05, ** p<0.01, *** p<0.0

Appendix (for the referees)

Table 8 - Results of the estimation with three-way interaction

Dep var: gEmp	**Baseline**			**Interacted**		
	(1)	(2)	(3)	(1)	(2)	(3)
Entropy	-0.000190			0.00208		
	(0.00264)			(0.00270)		
RV		-0.00356			-0.000806	
		(0.00373)	0.00395		(0.00396)	
UV			(0.00416)			0.00810
						(0.00449)
C	0.0250**	0.0255**	0.0250**	-0.00195	0.00104	-0.00337
	(0.00891)	(0.00891)	(0.00890)	(0.00852)	(0.00828)	(0.00847)
NVQ	-0.00203**	-0.00200**	-0.00203**	0.000193	0.000214	0.0000939
	(0.000760)	(0.000760)	(0.000759)	(0.000746)	(0.000746)	(0.000740)
HT_pat	0.000647	0.000646	0.000722	-0.000713	-0.000627	-0.000587
	(0.00152)	(0.00151)	(0.00152)	(0.00148)	(0.00148)	(0.00147)
LT_jobs	-0.000488	-0.000475	-0.000503	-0.000574	-0.000506	-0.000603
	(0.000640)	(0.000639)	(0.000639)	(0.000612)	(0.000610)	(0.000610)
Density	0.0000172	0.0000170	0.0000169	-0.00000926	-0.00000546	-0.0000157
	(0.0000212)	(0.0000212)	(0.0000212)	(0.0000152)	(0.0000146)	(0.0000153)
Entry	-0.00572	-0.00575	-0.00608	-0.00385	-0.00380	-0.00423
	(0.00463)	(0.00462)	(0.00463)	(0.00445)	(0.00445)	(0.00445)
Crisis	-0.00612*	-0.00615*	-0.00606*	-0.0205***	-0.0203***	-0.0209***
	(0.00264)	(0.00264)	(0.00264)	(0.00305)	(0.00304)	(0.00305)
Entropy*crisis				-0.00398		
				(0.00240)		
RV*crisis					-0.00507	
					(0.00397)	
UV*crisis						-0.00808
						(0.00459)
C*crisis				0.0267***	0.0210***	0.0300***
				(0.00680)	(0.00451)	(0.00809)
HT_pat*crisis				0.00346*	0.00328*	0.00329*
				(0.00135)	(0.00135)	(0.00131)
Entry*crisis				-0.0358	-0.0377	-0.0337
				(0.0321)	(0.0321)	(0.0321)
Entry*HT_pat*crisis				-0.135	-0.139	-0.125
				(0.0724)	(0.0724)	(0.0723)
Regional dummies	YES	YES	YES	YES	YES	YES
Constant	-0.0408	-0.0371	-0.0493			
	(0.0286)	(0.0277)	(0.0285)			
R-sq	0.12	0.12	0.12	0.23	0.23	0.23
Observations	747	747	747	747	747	747
Nr of regions	131	131	131	131	131	131

Estimated intercept and slope coefficients for each regressor with robust standard errors in parentheses.
Asterisks denote significance: * p<0.05, ** p<0.01, *** p<0.001