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Riccardo Cappelli
Department of Economics and Statisitcs *Cognetti de Martiis* , University of Turin

Fabio Montobbio
Department of Economic Policy, Università Cattolica del Sacro Cuore
ICRIOS, Bocconi University
BRICK, Collegio Carlo Alberto

Andrea Morrison
Department of Human Geography and Planning, Utrecht University
ICRIOS-Bocconi University

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Cappelli Riccardo[*], Montobbio Fabio[+] and Morrison Andrea[^]

[*] Department of Economics and Statistics "Cognetti de Martiis", University of Turin, Lungo Dora Siena 100/A, 10136 Turin, Italy. Email: riccardo.cappelli@unito.it. ORCID: https://orcid.org/0000-0001-7917-5142.

[+] Department of Economic Policy, Università Cattolica del Sacro Cuore, Milan; ICRIOS, Bocconi University, Milan; BRICK, Collegio Carlo Alberto, Turin. Email. fabio.montobbio@unicatt.it

[^] Department of Human Geography and Planning, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht; ICRIOS-Bocconi University, Department of Management and Technology, via Roentgen 1, 20136, Milano. Email: a.morrison@uu.nl

Abstract

We investigate the impact of the 2008 crisis to study the relationship between economic and technological resilience in 248 European Union regions. For economic resilience we measure the difference between the level of unemployment rate before crisis and the level of unemployment rate at its peak after the crisis — i.e., the unemployment resistance. Using European Patent Office patents, we look at all technological crises in each region since 1978 and build a variable of technological resilience measuring the historical ability of a region to maintain its level of knowledge creation in face of adverse shocks — i.e., the technological resistance. We find that technological resistance is a good predictor of economic resistance. In particular, our results show that (1) important interaction effects exist between technological resistance and human capital, (2) technological resistance and the level of human capital are less effective in protecting female and elder adult workers in an economic crisis and (3) important country level effects are present.

JEL classification: 033, R11, J64, J24

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1. Introduction

In May 2008 the unemployment rate for the EU-27 was at its minimum level. Between May 2008 and January 2013, it rose from 6.8 % to 10.9 %. After reaching its maximum value it declined back to 7.1 in January 2018. The crisis and the recovery periods were also evident at regional level and have affected the EU regions very differently over the last ten years. The economic downturn has dramatically hit some regional labor markets. The unemployment rate increased substantially not only in several Spanish and Greek regions, but also in many eastern regions of Bulgaria as well as in Baltic countries. Also, more innovative and advanced regions in Denmark, Northern Italy and the United Kingdom experienced a strong increase in their unemployment rates. In contrast some regions in Germany France and Belgium have continuously improved their economic conditions and local labor markets. All in all the impact of the crisis was very heterogeneous across EU regions (Sensier et al. 2016). The post crisis increase in the unemployment rate is often coupled with rising inequality, heterogeneous gender effects and deteriorating working conditions for young people (Verick 2009; Périvier 2014). Why is it that some regions have been able to quickly recover, some have failed to maintain their historical rates and others are lagging behind? Why are some regions more resilient than others in limiting the intensity of an economic shock and being able to invest and catch new economic opportunities? To what extent crisis and recovery had a different impact on the different components of the labour force at the regional level?

Evolutionary economic geographers and economists have focused on the capacity of regions to react to economic crisis, reshaping their economic structures and redesigning their institutional settings to exploit new growth path. This capacity is called regional resilience. There is a large amount of literature on this issue and it is possible to look at the concept of regional resilience from different perspectives (Boschma 2015; Bristow 2010; Bristow and Healy 2014; Crescenzi et al. 2016; Diodato and Weterings 2014; Fingelton et al. 2012; Martin 2012; Martin and Sunley 2014; Martin et al. 2015; Pendall et al. 2010).

This paper develops the literature on the resilience of regions by looking at the impact of the 2008 economic crisis on European regions and it does it in four distinct directions. First of all (1) we claim that economic resilience is strongly influenced by technological resilience. We consider that the relative capacity of regions to produce and create technological knowledge and to maintain this production and creation over time, in particular in periods of economic crisis, is a key determinant of economic resilience (Filippetti and Archibugi 2011; Balland et al. 2015). We measure the economic resilience with labour market variables as it is usually done in this literature (Diodato and Weterings 2014; Fingleton et al. 2012). We consider unemployment resistance as a key dimension of resilience and (2) we extend and articulate the concept tackling the heterogeneity of resilience according to different categories of the labor force. Specifically we consider age, gender and the duration of unemployment. In doing, so we aim at addressing the question of *who* is affected by the crisis (Martin and Sunley 2014), therefore which categories of workers are benefited in regions with high economic resistance. In addition (3) our point of departure is that the technological resilience of regions depends to a great extent on their technological history. In particular the ability of a region to absorb shocks and their speed of recovery depend upon the past ability to reorienting skills, resources and technologies. As a result we measure technological resilience with the ability of the regions to absorb and react to technological crisis (Balland et al. 2015). (4) Finally, within the context of rapidly changing economic environments, the human capital and the skilled labour force have to be considered a key ingredient to generate and accumulate knowledge to promote new recombinations and applications (Crescenzi et al. 2016).

In this paper we estimate a cross section of 248 EU regions to show the main elements that are associated with unemployment resistance after the 2008 crisis. Unemployment resistance is the difference between the level of unemployment rate before crisis and the level of unemployment rate at its peak after the crisis. We build an indicator, using patent data, of technological resistance based on the historical ability of the regions to react to technological crisis (Balland et al. 2015) and, controlling for many possible confounding factors, show that technological resistance is an important factor associated with unemployment resistance. We show also that this effect is particularly strong when coupled with a high level of human capital, at the same time human capital alone is not enough to guarantee low unemployment rates after the crisis. We show also that the role of technological resistance is particularly important for regions that have a relatively more solid initial economic conditions and has a larger impact on the male and young labour force and on long-term unemployment. Importantly we observe very strong country fixed effects. For some weak regions and for females and elders, country effects are the most significant variables affecting unemployment resistance. This latter finding suggests that the literature on regional resilience should take into account the complex and diverse interactions with the institutions and policies at country level.

The paper is organized as follows. First, in Section 2 presents the theoretical background and the existing empirical evidence. Sections 3 discusses our theoretical arguments concerning the determinants of economic resilience. Section 4 introduces data and methods, which include the measurers of economic, technological resilience and human capital and the econometric specification. Section 5 presents the results. Section 6 provides a conclusion and a discussion of our findings.

2. Theoretical background and empirical literature

Since the inception of the Great Recession a proliferation of theoretical and empirical studies investigates the causes and impact of the economic crisis (Boschma 2015; Bristow 2010; Bristow and Healy 2014; Crescenzi et al. 2016; Diodato and Weterings 2014; Filippetti and Archibugi 2011; Fingelton et al. 2012; Martin 2012 Martin and Sunley 2014; Martin et al. 2015; Pendall et al. 2010; Rocchetta and Mina, 2017). In particular, the concept of *resilience* is a widely used buzzword both in academic and policy debates to understand how countries and regions cope with economic shocks.

In the literature at least three different notions of *resilience* have been put forward and popularised (Pendall et al. 2010; Simmie and Martin 2010): an engineering interpretation, an ecological interpretation and a complex adaptive interpretation.

The former conceptualise resilience in terms of bounce back to a pre-existing state. Such an interpretation assumes that economic systems are always on a long-term equilibrium path, which is occasionally broken up by shocks. Along this line of reasoning, regions are resilient when they are able to bounce back to the pre-crisis state, which represents their long-term equilibrium.

An ecological interpretation focuses on the ability of a system to absorb a shock. Differently from the previous definition, it assumes that a resilient system is able to shift towards a new state of equilibrium. According to this definition, a resilient region is able to resist and absorb a shock. Also in the ecological definition (in line with the engineering one) resilient regions are able to accommodate a shock, while adapting (with limited changes) their economic structure, so that the core activities and specialisation are unaltered.

Finally, the third definition focuses on the capacity of regions to adapt and evolve in response to the changing external conditions. In this view, a resilient region changes its functions and structure in order to reach its long-term growth path and, differently from the other ones, it focuses on the long-term adaptability of a region (Boschma 2015; Martin and Sunley 2014). According to this latter view, short term adaptation might even be detrimental for regions, as it reinforces the structural conditions that have possibly led to the crisis-event. The evolutionary view indeed highlights the potential trade-off between short-term adaptation and adaptability, where the former represents the tendency of a system to react to external challenges by reinforcing the pre-existing economic structure and specialisation; while the latter represents the ability of a region to turn a crisis into an opportunity for changing the actual economic structure and develop new activities. This view resonates in the idea of Schumpeter, that a resilient region takes advantage of the gales of creative-destruction generated by a crisis (Schumpeter 1942).

Moreover, four different dimensions of resilience have been discussed by the literature (Martin 2012): resistance, recovery, renewal and re-orientation. The first dimension indicates how vulnerable is a regional economy to a recessionary shock; the second dimension describes the speed at which such regional economy recovers from a shock; the third one and fourth ones indicate respectively the *extent* and *degree* of structural transformation needed by the regional economy to regain growth.

Early empirical studies have mainly focused on the short-term impact of the crisis. A seminal work by Fingleton et al. (2012) shows that the UK regions show large differences in their ability to recover from shocks. Studying crisis events for a long time period (1970-2010), they observe that a short-run negative response to an unemployment shock is on average rapidly followed by employment growth in the longer run. However, this is mainly driven by the positive response of a bunch of regions, while others reacted negatively. However, this study does not dig further in the causes of resilience.

Another stream of literature, mainly drawing on evolutionary theorizing, has focused on the structural factors that allow regions to resist shocks and move towards new growth paths[1]. This approach, by building on the Schumpeterian idea that crises are inherent features of capitalisms, assumes that economic systems, and accordingly their industrial structure, have to constantly cope with the upturns and downturns of business cycles (Martin et al. 2015). Empirical studies using an evolutionary approach investigate regional resilience using a variety of economic phenomena besides standard performance indicators of an economy (e.g. GDP, unemployment), such as firms birth (Huggins and Thompson 2015); patenting dynamic (Balland et al. 2015), or the dynamic of specific industries (Doussard and Schrock 2015). These empirical analyses have generated rich empirical evidence on specific economic context (e.g. sectors, countries); however they don't provide a comparative perspective, in particular on European regions.

Only a few empirical works have so far looked at the differential impact of shocks across European regions or countries. An early work of Groot et al. (2011) has investigated the differential impact of the 2008 crises across European countries. These differences are related to a number of potential macro factors, which have possibly favoured the transmission of the crisis. For example, they show that financial factors (e.g. government support to banks) played a major role, though their impact differed considerably across countries. In line with previous studies, they also found that trade openness represented an important transmission channel. Adding a wide range of institutional factors to the analysis, they show that their role differed greatly across EU countries.

A comparative analysis at regional level can be found in Sensier et al. (2016). This work provides a new methodology to measure resilience in terms of resistance and recovery from a sock. By focusing on 289 NUTS2 regions of 31 European countries over the period 1922-2011, and looking at the 2008 crisis, they show that the time of

[1] See special issues of the journal *Cambridge Journal of Regions, Economy and Society* (Volume 3, Issue 1, 2010; Volume 8: Issue 2, 2015).

entry into crisis differ across regions: for example a few entered as early as 2006, while only in 2009 most EU regions (i.e. 238) experienced fully the effect of the economic crisis. Also exit from the crisis shows lots of heterogeneity. In 2009, some regions already showed signs of recovery, while by 2011 many did not show signal of recovery. So, the map of resilient regions is very diverse: one third proved to be resilient to the 2008 crisis, i.e. they did not experience a fall in employment; while another third was hit, but experienced a stop in employment fall by 2011; the remaining third part of regions was still suffering unemployment growth instead by then. The analysis however focuses on revealed resilience only, and in the words of the authors “It does not in and of itself tell us anything about resilience capacities or why different regions exhibited different resilience outcomes in relation to the economic shocks in question” (pag. 148).

Finally, Crescenzi et al. (2016) adopt a cross regional perspective for EU regions and at the same time they estimate the regional determinants of resilience. This work focuses on the short-term effects of the 2008 crisis on gross value added and unemployment, so it conceptualises resilience as resistance to shocks. Explanatory factors include both national macro-economic determinants (e.g. FDI, institutions, public debt) as well as regional indicators of competitiveness (e.g. economic structure, human capital, innovation). Looking at the regional factors only, their analysis shows some interesting and perhaps unexpected findings. In particular they show that human capital and innovation (captured by R&D intensity) had opposite effects on regional performance during the crises. While human capital is positively associated with regional gross value added, the opposite happens for R&D. According to the authors these findings signals that “(…) regional resistance is not technology-driven innovation (captured by formalized R&D investments), but rather a generally innovation- prone environment (captured by the abundance of human capital) that can facilitate process and organizational innovation (…).” (pag. 25). On the contrary, the same variables show reversed signs when the impact on employment is estimated, though are both statistically insignificant.

Similar to Crescenzi at al. (2016), our study provides comparative evidence of the impact of the 2008 crisis on EU regions. In the section below, we provide our framework of analysis and how we contribute to the extant empirical literature.

3. Regional Resistance: the role of innovation and human capital.

The impact of the 2008 crises was spatially uneven. Countries and regions had different abilities to cope with economic shocks and recover from them. A variety of factors have been put forward to explain why some regions might deal with shocks better than others (Martin 2012; Crescenzi et al. 2016; Groot et al. 2011). They might include the region's economic structure, which refer to the degree of specialisation or the relative share of manufacturing vs construction sector in a region; the institutional environment, for example how flexible are the national or local labour markets or how effective is property rights enforcement; the degree of local and international interconnectedness as measured by trade flows or sectoral linkages (MacCann and Argiles 2015; Diodato and Weterings 2014) and, finally, human capital and innovation intensity (Martin 2012; Martin at al. 2014).

Our primary interest goes to this latter group of factors, we are interested in understanding the role of human capital and innovation for regional resilience, where resilience is conceptualised in terms of *resistance* to shocks, that is the sensitivity of regions to economic shocks (Martin 2012).

Theoretically, we adopt an evolutionary interpretation of resilience. The resistance to shocks depends primarily on the adaptability of the regional innovation system to external changing conditions. As discussed below, this is captured by a measure of technological resilience, which describes the innovation dynamics within regions.

The role of innovation during economic fluctuations like the recent crisis has received some attention in the empirical literature but it's still underdeveloped. Some evidence suggests that regions relying on a strong innovation system will accommodate better and respond more promptly to an economic shock. A recent study of Filippetti and Archibugi (2011) has shown indeed that countries with stronger innovation systems have suffered less in terms of innovation performance from the 2008 crisis. Moreover, Lucchese and Pianta (2011) have shown that innovation activities support economic growth of industries during economic upswings, and alleviates the negative impacts of economic downswings. Also at regional level, there is some evidence showing that the presence of high skilled workers allows local economic system to adjust more promptly to the changes imposed by a shock (Crescenzi et al. 2016).

More in general, it is widely shared that economic systems (i.e. regional economies) endowed with strong and/or diversified knowledge assets have higher opportunities to recombine their knowledge and come up with novel products or processes (Boschma 2015). Under a crisis event, regions specialised in more dynamic sectors (e.g. high tech) will be less affected, since they operate in markets segments or industries which are overall more dynamic than average, and even if hit by the crisis, they will have higher chances than average region to reconfigure themselves and enter new promising markets/industries (Rocchetta and Mina, 2017).

Moreover, we can expect that innovative regions tend to attract more talented workers. In close analogy with sectors, it can be argued that high skilled workers show higher adaptability, so they switch more easily from sectors in crisis to growing sectors. These workers can possibly upgrade faster their skill profiles and in turn adapt quicker to the new market requirements (Crescenzi et al. 2016). Therefore, a region endowed with a higher level of human capital might signal higher resilience to economic shocks.

It has been recently found however, that innovation intensity, as compared to human capital, might react more slowly to exogenous shocks since technological change (and related socio-institutional infrastructure) requires time to unfold and materialise, while on the other side instead, workers can acquire new skills and de-learning old ones rather quickly (Crescenzi et al. 2016). We will then explicitly address this paradox and check under which specific conditions it holds.

It can be argued that regions differ not only in the size of technological capital, but also in their capacity to adapt their technological assets (Kogler et al. 2013). For example, Balland et al. (2015) show that the technological resilience, i.e. the capacity to sustain the development of innovation activities facing an economic shock, of US cities is affected by factors like the composition of the internal knowledge base, the connectivity to external innovation systems and the institutional environment. We borrow from Balland et al. (2015) this concept of technological resilience - and the related indicator - as it allows to capture not only the innovative capacity of regions (though resilient regions are not necessarily the most innovative), but more than that how they are able to reorient skills, resources and technologies over the long-run. This conceptualization of innovative capacity seems to better capture, as compared to a standard measure of technological capital, the evolutionary concept of resilience as adaptability. The idea behind it is that regional innovation systems with strong long-term adaptive capacity in their technological structure would show also a higher capacity to cope with unemployment shocks.

Moreover, it can be argued that innovative regions can recover more quickly than non-innovative regions in particular when high levels of human capital are present. Human capital, new skill formation and the presence of high innovative sectors can positively coevolve generating a fast match between skills and jobs. However, an opposite scenario can emerge if strong human capital is combined with weak regions. A skill matching problem will delay the recovery of those regions.

We will also focus on the heterogeneous effects that shocks can have on the different components of the labour market, so addressing the question of *who* is affected by the crisis (Martin and Sunley 2014) and which categories of workers are benefited in regions with high economic resistance. The crisis can indeed affect different components of the job market asymmetrically (Verick 2009). Our attention goes to three broad categories that characterize the labour force: age, gender and unemployment duration. Labour market outcomes of young workers are more sensitive to business cycle fluctuations than labour outcome of older workers because young workers lack skills, work experience, job search abilities and the financial resources to find employment (ILO 2009; Verick 2009). On the other side, aspects like the gender segregation of labour markets, the role of women as cheap substitute workers and flexible labour supply might result in different responses (labour market outcomes) to economic cycle fluctuations for males and females (Rubery 1988). Finally, the variation in the average duration of unemployment is counter-cyclical (Hal Sider 1985) and must be reflected in variation of the share of long-term unemployment. The heterogeneous effects of economic shocks push towards a consideration of the concept of resilience that takes into account the distributional aspects (Martin and Sunley 2014). In weak labour market conditions is difficult for anyone to find a new job, but factors like human capital depreciation and the stigma associated with the lengthen of unemployment (Blanchard and Diamond 1994) reduces extremely the probability to find a job for long term unemployed. Furthermore, for youth people the failure to find a first job or to keep it might permanently compromising their employment prospects and earnings capacity (Scarpetta et al. 2010).

4. Methods, Data and Variables

This paper constructs a set of variables for the regions of the European Union's 27 countries relying on two databases. EUROSTAT's regional database provides the main economic and demographic variables used in the analysis (e.g. the unemployment rates for the period 2007-2016; the shares of population aged 25-64 with a tertiary education in 2006[2]; the population in 2006; the shares of employees in agriculture, manufacturing, construction and services sectors in 2006). In addition, the ICRIOS-PATSTAT database on EPO patent applications for the period 1978-2010 (see Coffano and Tarasconi 2014) is used to construct the variables related to the technological activities of regions (e.g. stock of patents in 2006, the Herfindhal index of technological diversification in 2006 and the variable used to measure the technological resistance of regions explained below)[3]. The initial database contains 270 NUTS2 regions (EUROSTAT 2011) of 27 countries. However, twenty-two regions are excluded from the analysis because of data constraints[4]. The final sample contains 248 regions of 26 countries (i.e. the EU27 countries excluding Slovenia).

4.1 Unemployment resistance

Resistance is a dimension of resilience and represents the depth of reaction of a region's economy to a shock (Martin and Sunley 2014). In this paper the resistance of

[2] Tertiary education is defined according to the International Standard Classification of Education (ISCED) levels 5, 6, 7 and 8 (short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, doctoral or equivalent level).

[3] As standard in the literature (see e.g. Cappelli and Montobbio 2016), patents are attributed to regions using the inventors' addresses.

[4] Nine regions (ES63, ES64, FI20, FR83, FR91, SI01, SI02, UKI1 and UKI2) are discarded because of missing data on unemployment rates. For three regions (FR92, FR93 and FR94) there are no information about human capital. Finally, ten regions (DE13, DE60, DK01, EL22, EL41, ES51, FI19, ITH5, PT20 and SK02) are discarded because no technological recession phases are observed for these regions (see below). As a robustness check, additional estimates are performed including the latter ten regions.

a region is measured by the difference between the level of unemployment rate before crisis and the level of unemployment rate at the peak of the shock-induced increment. In line with the existing literature (see e.g.: Crescenzi et al. 2016; Martin et al. 2015), we use the year 2008 as starting year of the recession period. The resistance of region i to an increase in the unemployment rate ($UNEMPres_{i,2008-2016}$) is computed in the following way:

$$[1]\, UNEMPres_{i,2008-2016} = -\log\left(maxUNEMP_{i,2008-2016} / UNEMP_{i,2007}\right)$$

where $maxUNEMP_{i,2008-2016}$ is the maximum unemployment rate observed during the period 2008-2016 and $UNEMP_{i,2007}$ is unemployment rate in 2007 of a given region i. Note that higher values of $UNEMPres_{i,2008-2016}$ correspond to lower increases in the unemployment rates during crisis and, thus, higher regional unemployment resistance.

Figure 1 shows the log of unemployment rate in 2007 (i.e. the log of $UNEMP_{i,2007}$) (panel a) and the unemployment resistance during crisis for the European regions ¿¿) (panel b). Figure 1 (panel b) shows that the most performing regions (i.e. regions with the lowest increase in the unemployment rates) are located mainly in Germany and Poland, while the most severely hit regions are located mainly in Greece, Ireland, Italy, Spain and Baltic states. All the other regions are in between these two groups of regions with strong opposite performance. Overall, it emerges a strong country effect, which will have to be accounted for in empirical analysis.

Data reported in Figure1 (panel a) suggests also that the regional performance during the crisis is affected by the initial level of unemployment. Some regions had a high (low) initial level of unemployment combined with a relatively good (low) performance during the crisis period. Overall, European regions show a high degree of heterogeneity. For example, some northern Italian region like Piedmont and Lombardy have a low unemployment rate in 2007 and, at the same time, are among the most hit by the 2008 crisis. On the other side, quite a few regions in Poland show high rates of unemployment in 2007, but also a high unemployment resistance.

- Fig. 1 Panel a) and b) about here -

4.2 Technological resistance

As underlined above, we argue that it is not the intensity of technological capital *per se* to influence the unemployment resistance of regions, but the characteristic of this capital to react facing adverse condition. Then, we build an index that measures the capacity of regions to have limited downturns in the production of innovations during technological crises. For that, we use a modified version of the methodology adopted by Balland et al. (2015). This procedure uses the time series of yearly regional patent data to capture the dynamics in the regions' production of inventions. These time series may be viewed as a continuum of local maxima (peak) and local minima (trough) that divide the regional patent series into periods of technological growth (from a trough point to a peak point) and technological crisis (from a peak point to a trough point). Focusing on the technological crisis periods, the reduction in the number of produced patents from the peak to the trough points is used to measure the intensity of the technological crisis and, thus, to capture the degree of resistance to technological crisis.

More formally, in line with Balland et al. (2015) we use an adapted version of the algorithm developed by Harding and Pagan (2002) on the time series of yearly regional patent data for the period 1978-2010 to identify the turning points, i.e. the peak and trough points, in the time series. This algorithm singles out the turning points ensuring that peaks and troughs alternate and specifies a minimum duration of the phases (period between a peak and a trough or vice versa) and cycles (period between two peaks or troughs). In particular, we require that the duration of phases and cycles is, respectively, 2 and 5 years at least (see Balland et al. 2015). Specifically, let $PAT_{i,t}$ to be the number of patents of region *i* at time *t*, a peak $\left(PAT_{i,t}^{peak}\right)$ occurs at time *t* if $\left(PAT_{i,t-2}+PAT_{i,t-1}\right)>PAT_{i,t}^{peak}<\left(PAT_{i,t+1}+PAT_{i,t+2}\right)$, while a trough $\left(PAT_{i,t}^{trough}\right)$ occurs at time *t* if $\left(PAT_{i,t-2}+PAT_{i,t-1}\right)<PAT_{i,t}^{trough}>\left(PAT_{i,t+1}+PAT_{i,t+2}\right)$. As an example, Figure 2 shows the peak and trough points identified for the German region Dusseldorf.

- Fig. 2 about here -

Once identified the turning points, for each technological recession phase ending before the year 2006,[5] the number of patents at the peak (i.e. the last period before the starting of a technological recession phase) and the number of patents at the trough (i.e. the ending period of a technological recession phase) are used to compute the peak-trough ratio ¿¿) in the following way: $PTR_{i,t} = \left(PAT^{peak}_{i,t} - PAT^{trough}_{i,t} / PAT^{peak}_{i,t} \right) * 100$. The peak-trough ratio ranges between 0 (if the region produces the same number of patents at the peak and the trough point) and 100 (if the region does not develop any patent at the trough). The peak-trough ratio is used by Balland et al. (2015) to measure the intensity of technological crisis. In order to have a variable for which higher values correspond to higher level of resistance to technological crisis, we take the opposite of the peak-trough ratio: -$PTR_{i,t}$. Since regions might be interested by two or more technological recession phases during the period 1978-2006, the empirical analysis uses the mean value of the opposite values of the regional peak-trough ratio observed for the period 1978-2006 to measure the regions' degree of resistance to technological crisis ($TECHres_{i,2006}$).

Figure 3 shows the technological resistance level ($TECHres_{i,2006}$) for the European regions. Regions with the highest level of technological resistance are mainly located in the Central-Northern European regions. Moreover, the map shows that in Germany, Netherlands, Spain, Portugal and the Eastern European countries, regions are rather homogeneous, while other countries like Italy, Sweden and United Kingdom show a higher intra-national regional variance.

- Fig. 3 about here –

[5] This paper allows technological recession phases to start in 1978 because of data truncation before 1978. For the last period considered, i.e. the year 2006, only recession phases ending before 2006 are considered to avoid overlapping periods with those used to calculate the unemployment performance over the recent economic crisis. This is done to mitigate the endogeneity bias. Additional robustness checks are performed to ensure the validity of the main results do not rely on the way is computed the technological resilience measure.

Table 1 shows the mean value of technological and unemployment resistance for five group of regions ranked according to their levels of technological resistance. It suggests that, on average, higher values of technological resistance are associated with higher values of unemployment resistance.

- Table 1 about here -

4.3 Human capital

Finally, we look at the performance of regions distinguishing between regions with low and high human capital before the 2008 crisis. In particular, we measure human capital in 2006 ¿¿) as the percentage of people aged 25-64 with a tertiary education. The median value of $HUMANcap_{i,2006}$ is used to discriminate between the two groups of regions. The percentage mean value of unemployment resistance is -43.3% for regions with low human capital and -52.9% for regions with high human capital.[6] It follows that, on average, regions with high level of human capital are more affected by the crisis than regions with low level of human capital. In addition for each group, using the median value of $TECHres_{i,2006}$ we distinguish between regions with low and high level of technological resistance. Table 2 shows the mean value of unemployment resistance ($UNEMPres_{i,2008-2016}$) for these four groups. It clearly emerges that, on average, regions with a high level of technological resistance perform better irrespectively of the level of human capital. On the other side, the difference in performance is greater for the group of regions with high human capital. In sum Table 2 suggests that important interaction effects exist between technological resistance and human capital. In fact, technological resistance improves significantly the unemployment resistance in particular in those regions with high levels of human capital.

- Table 2 about here -

[6] The result of a t-test show that the two mean values are significantly different at 1% level.

4.4 Methodology

We model regional resilience using unemployment resistance. Our two main variables of interests are: technological resistance ($TECHres_{i,2006}$) and human capital ¿¿). As a result$UNEMPres_{i,2008-2016}$ is modeled using the following equation[7]:

$$[2]UNEMPres_{i,2008-2016}=\alpha+\pi\log\left(UNEMP_{i,2007}\right)+\beta\,TECHres_{i,2006}+\varphi\,HUMANcap_{i,2006}+\Omega\,RECyears_{i,2006}+$$

Equation [2] represents the main model. Additional regressions are performed on a model that includes the interaction between technological resilience and human capital, as suggested by the descriptive evidence in Table 2. We control in the regression analysis for a number of factors that affect $UNEMPres_{i,2008-2016}$ and could be correlated with $TECHres_{i,2006}$ and $HUMANcap_{i,2006}$.

In particular, we consider those regional characteristics which affect the regional performance during the crisis period. We include the number of years in technological recession $\left(RECyears_{i,2006}\right)$ because the intensity of a crisis might be affected by the duration of the crisis. This variable is constructed summing the number of technological recession years during the period 1978-2006. Again, all the technological recession phases are considered for regions that experienced multiple recession phases. This variable control for the vulnerability of the regional technological system (Balland et al. 2015). The patent stock per capita ($PATpc_{i,2006}$) and the Herfindhal index of the shares of patents developed in IPC (international patent classification) four-digit technology fields ($HERFtech_{i,2006}$) are, respectively, used to control for the size and specialization of the region's technological capital. The GDP per capita in 2006 ($GDPpc_{i,2006}$) is included to control for the overall level of economic development. The logarithm of population in 2006 ($POP_{i,2006}$) controls for the size of the

7 Equation [2] can be rewritten as: $[2]-\log\left(maxUNEMP_{i,2008-2016}/UNEMP_{i,2007}\right)=\alpha+\pi\log\left(UNEMP_{i,2007}\right)+x'\beta+\varepsilon_i$. Where x' is the vector of independent variables. An analogous specification would be: $[2a]\log\left(maxUNEMP_{i,2008-2016}\right)=-\alpha+\left(1-\pi\right)*\log\left(UNEMP_{i,2007}\right)-x'\beta-\varepsilon_i$. So in fact we are estimating the determinants of the maximum unemployment rate between 2008 and 2016, controlling for the level of unemployment in 2007. The post-crisis recovery period is not included.

region and a dummy for capital regions ($CAPITAL_{i,2006}$) is included as control because capital regions tend to outperform other regions thanks to several factors like the higher concentration of research institutes and high value-added activities (Hoekman et al. 2009; Dijkstra et al. 2015). The crisis might have affected economic sectors in different way and, thus, this paper includes as control variables the shares of employment in agriculture ($AGRIC_{i,2006}$), manufacturing ($MANUF_{i,2006}$) and construction ($CONSTR_{i,2006}$) (services sector is used as reference category). Finally, country dummies ($COUNTRY_i$) are included to control for all country level unobserved characteristics.

All estimates are performed using OLS regressions. To facilitate the comparison of the regression coefficients, the continuous independent variables are standardized dividing them by two times the sample standard deviation, while the dichotomous independent variables are centered around their sample mean (i.e., demeaned) (Gelman 2008). The adopted linear rescaling changes the coefficient values of the independent variables, but does not change the associated t-statistics and p-values.

5. Results

Table 3 shows the descriptive statistics of the unstandardized regression variables and Table 4 shows the results of the OLS estimates.

- Table 3 about here -

Models in columns 1a, 2a and 3a show the effect of technological resistance, while the interaction effect with human capital is shown in models 1b, 2b and 3b. Models 1a and 1b show the results controlling only for the unemployment rate in 2007. Models 2a and 2b extend the basic models by adding all the other control variables with the exception of the country dummies. Models 3a and 3b show the results when also the country dummies are included.[8]

[8] For each model, a variance inflation factor test is performed. The results range from 1.08 of the basic model (Model 1a) to 3.10 of the most extended model (Model 3b). Therefore, we conclude that multicollinearity is not a concern for our models.

In all models we find a significant and positive effect of technological resistance ($TECHres_{i,2006}$). Technological resistant regions are also those which experienced a lower increase in the unemployment rates after the 2008 crisis. This result suggests that the unemployment resistance during the recent crisis is associated with the regions' capacity to maintain the levels of knowledge creation in face of adverse shocks. This capacity might reflect the ability of regions to reconfigure the technological structure by recombining the existing technologies in novel ways (Balland et al. 2015). This interpretation is confirmed by Archibugi et al. (2013) that show that companies pursuing an explorative strategy towards new product and market development are those with better innovation performance during the recent crisis. Notably this result is robust to the inclusion of country fixed effects (see Models 3a and 3b).

The coefficient of the human capital variable ¿¿) is negative and significant in all specifications, but when countries dummies are included in the model. In this latter case, the coefficient of human capital is not statistically significant (see Models 3a and 3b), suggesting that human capital alone is not enough to ensure unemployment resistance. A positive effect of human capital on unemployment resistance appears only when is interacted with the variable of technological resistance (see Model 3b). Overall, these results are in line with those of some recent studies (Ramos et al. 2009; Cadil et al. 2014), which stress that higher human capital endowments do not guarantee low unemployment levels both in economic stable and crisis periods. Our results add to that showing that regions' human capital must be supported by an adequate technological capacity which is resilient to shocks. Similarly, the positive and statistically significant effect of the interaction term between technological resistance and human capital $\left(TECHres_{i,2006} * HUMANcap_{i,2006}\right)$ suggests that technological resistance is particular effective at facing an economic downturn, when the region has a high level of human capital.

The inclusion of country dummies is particularly important in the model. We observe that R-squared increases from 0.62 up to 0.93. In addition the estimated effect of technological resistance decreases from 0.24 to 0.13 (Models 2b and 3b). Almost half of the effect of technological resistance is captured by country level variables. On the one side an important portion of the technological resistance at the regional level is affected by the characteristics of the country. Institutional and policy factors at country level clearly affect regional innovation systems and how they contribute to local unemployment. Secondly, country dummies are almost always statistically significant. As shown in Table 7 in the Appendix B, unemployment resistance is particularly low for Estonia, Greece, Spain, Ireland, Lithuania, Latvia, Portugal and Italy, as compared to Germany, the reference category.

The estimation of Model 3b shows also that the log of the unemployment level at the initial period ($UNEMP_{i,2007}$) is statistically significant and has a positive sign. Despite the crisis, during the period of investigation a convergence process takes place: regions with higher unemployment rates, *ceteris paribus*, show higher unemployment resistance. We also find a positive and significant effect of GDP per capita ($GDPpc_{i,2006}$). This means that, *other things being equal,* richer regions where less affected by the recent economic crisis, at least in terms of unemployment rates. In addition, there is a negative and significant effect of the dummy capital regions (*CAPITAL*¿¿*i,*2006)¿, i.e. capital regions suffered more than others. A possible explanation can be attribute to the volatile effects of agglomeration economies which render capital regions more sensitive to severe shocks like the recent crisis (Dijkstra et al. 2015). Lastly, patent stock per capita ($PATpc_{i,2006}$) is positive but not significant. This result underlines that is not the technological capital *per se* to matter, rather how it is adaptive and resistance to recurrent crises.

Several additional estimates are performed controlling for (1) the distribution extreme-values of technological and unemployment resistance, (2) the potential biases for the inclusion of regions with a positive value for the dependent variable (i.e. the invulnerable regions), and for the exclusion of the regions with no technological recessions before 2006, (3) the potential biases in the measurement of the regions' technological resistance capacity, (4) the regions' pre-crisis unemployment trend, (5) uncertainty about the exact starting date of the regions' crisis periods (Sensier et al. 2016). Overall, these robustness checks validate our main results (for further details, see the Appendix A).

- Table 4 about here -

It is plausible to assume that the crisis unfolded differently in each region depending on their initial economic conditions. In particular, we can expect that the role of technological resistance and human capital in attenuating the economic effect of the crisis could be larger in healthier regions. To test this possible scenario, we distinguish between regions according to the pre-crisis level of the unemployment rates. We use the median value of the unemployment rate in 2007 as a cut off value. Table 5 reports the results.

Models 4a-7a (4b-7b) refer to those regions with a level of unemployment rate in 2007 above (below) the median value; Models 6a, 6b, 7a and 7b include the interaction between technological resistance and human capital; Models 5a, 5b, 7a and 7b include country dummies, (Germany is used as reference category, see in Table 7 in the Appendix B for the values of the estimated country fixed effects).

We can highlights three main findings. First of all the positive effect of technological resistance on economic resistance tends to be confirmed. Considering the sample of regions with a lower median level of unemployment rate in 2007, the positive and significant effect of technological resistance in Model 5b is larger relatively to the full sample. Conversely, regions with a upper median level of unemployment rate in 2007 have a positive and significant effect of technological resistance (see Models 4a and 6a). As above, once country dummies are included in the model specification, the effect of technological resistance becomes statistically insignificant (Model 5a and 7a). Interesting, these results suggest that for disadvantaged regions, country characteristics are more important than their technological resistance.

Second, the interaction term between human capital and technological resistance is positive and statistically different from zero only in those regions that have a lower unemployment rate in 2007. So, our results indicate that only the more solid regions are able to exploit the joint effect of high levels of human capital and the ability to react in terms of technological capacity. Finally there is a significant negative effect of human capital (see Model 4b and 5b), suggesting that higher human capital endowments might results in higher unemployment rates if the human capital is not supported by a technological capital that is resistant to crisis[9].

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[9] In some regions skilled workers could crowd out unskilled workers (Ramos et al. 2009; Cadil et al. 2014). After an adverse economic shock, regions with a high level of human capital but economically weak could suffer from a displacement of unskilled

With regards to the other control variables, we find that technological specialization has a positive effect in poorer regions (see Model 7a) and a negative effect for richer regions (see model 7b). For the poorer regions, the effect is driven by the highest technologically specialized regions and when we exclude regions located in the last percentile of the Herfindhal technological index, the coefficient is no longer statistically significant. For the richer regions, the results suggest that diversified regions are less affected by economic shocks since technological diversification reduces the regions' exposure and sensitivity to different types of shocks (Frenken et al. 2007). Moreover, we find, as expected, a negative effect of the construction industry, but only for poorer regions (see Model 7a); and a positive effect of the agriculture industry, but only for the richer regions (see Model 7b).[10] The initial economic condition (GDP per capita level) affects regional performance only within the group of richer regions (see Model 7b). As expected, the country dummies are negative and statistically significant in most of the cases for both samples (see Table 7 in the Appendix B).

- Table 5 about here -

Finally, we analyze whether the effects of technological resistance and human capital on unemployment resistance differ by gender, age (i.e. young: age 15-24 vs. elders: age >24) and unemployment duration (i.e. long-term unemployed: unemployment condition > 12 months). For each group of unemployment, we compute the corresponding unemployment resistance (i.e. the dependent variable) and the log of unemployment rate in 2007 (the initial level of unemployment as control variable). Then, a new set of estimates are performed keeping all the other independent variables unchanged. Table 6 reports the results for models that do not include the interaction term (Models 8a-12a) and models that include the interaction term (Models 8b-12b). All regressions in Table 6 include the full set of control variables and country

jobs by skilled workers. Possibly this could increase, especially for the less educated group of population, the unemployment level. However, regions with a technological resistant capital are less affected by these effects because high-skilled people are more likely to keep their jobs, and, at the same time, there is less pressure, in terms of stagnating labour demand, for the low-skilled workers.

[10] In this regard, the existing literature has underlined the role of agriculture as a buffer against unemployment for the most vulnerable groups in society (see e.g.: Signorelli and Perugini 2010).

dummies. Sample sizes differences between models are due to data constraint, i.e. the lack of information on the unemployment rates of the considered unemployment category[11].

These results suggest that technological resistance and its interaction with human capital have a positive effect especially upon the unemployment resistance of young male and on long run unemployed. With regards to the gender category, Models 8a and 8b show that technological resistance and its interaction with human capital have a significant positive impact on unemployment resistance only for males.[12] Within the age category, technological resistance and its interaction with human capital are both positive and significant for young people (see Models 10a and 10b), while only the interaction term exerts a positive significant effect for the elders (see Model 11b). Finally, we observe a statistically significant effect of both technological resistance and of the interaction term on the unemployment resistance of long-term unemployed (see Models 12a and 12b).

Interestingly, young and male people are two categories severely hit by the recent economic crisis (Verick 2009). However we underline that technological resistance and its interaction with human capital seem to be less effective in reducing the unemployment growth of female and adult workers when a region is hit by an economic downturn. If this latter effect is particularly strong and persistence, this finding suggests that the crisis can potentially widen the gap between advantaged and disadvantaged groups in the labour market.

- Table 6 about here -

6. Conclusions and Discussion

[11] To compare the effects of technological resistance and human capital on unemployment performance across the different unemployment categories, we perform additional estimates for the subsample of 196 regions for which we have unemployment data for all the categories. In general, the estimates results (see Table 8 in the Appendix C) are similar to those in Table 6 (except for the significance level which is lower in some cases) confirming that technological resistance has a significant role above all for young and male people.

[12] We also perform estimates substituting the aggregated human capital with the human capital of males (females) in Models 8a and 8b (Models 9a and 9b). The estimates results (available from the authors upon request) are very similar.

This study investigates the determinants of regional resilience in the EU to understand the role of technological resilience and human capital during the of the 2008 crisis. Our analysis allows to grasp a number of interesting issues not fully developed in the regional resilience literature. First of all we tackle directly the relationship between technological resilience and economic resilience. To measure technological resilience we adopt a measure based on Balland et al. (2015). We identify for each European region their technological crises defined as a decline in the patenting activity. We exploit the distance between the peak and the trough in the time series to study the relative capacity of a region to maintain its technological activity over time in particular when the region faces adverse shocks. We look at all technological crises in the regions since 1978 with the underlining assumption that the past capacity of a region to absorb shocks and remain innovative and competitive is a way to capture technological resilience. For economic resilience we select the dimension of unemployment resistance. We analyze the impact of the 2008 crisis in European regions and we show that technological resilience is a good predictor of economic resilience. There is a strict link between the past ability of regions to sustain the production of knowledge and the ability of a regional economic system to resist in term of unemployment rates to the 2008 crisis. This occurs for many European regions and, in particular, for those that were more economically solid before 2008.

A second important issue is human capital. We show that there is a process of reciprocal reinforcement between the technological capacity of regions to absorb shocks and the level of human capital at the regional level. On the one side technological resistance is more effective if in the region there are high levels of human capital. On the other side human capital alone, after a crisis, is not enough to sustain the economic regional system if it’s not coupled with a more general ability of the region to re-orienting innovative resources and technologies to shape new growth path. This ability is to a great extent a legacy of the past technological history.

Third, economic resilience in the form of unemployment resistance encompasses heterogeneous outcomes for the different components of the labour force. We show that the effectiveness of technological resistance and human capital to reduce the unemployment impact of the 2008 crisis regards in particular male and young workers and affects long-term unemployed. As a consequence at a regional level technological resistance and the level of human capital are less effective in protecting female and elders after an economic crisis.

Finally, regions are deeply embedded in the national institutional set of norms, regulations and policies. In line with other studies (Crescenzi et al. 2016; Groot et al. 2011) our findings show that in term of economic regional resilience, country effects are extremely relevant. We believe that the complex interaction between the regional development paths and the institutional and policy variables at country level are a key aspect that should be taken up for further research by the buoyant stream of literature on regional resilience.

Appendix A: Robustness checks

Various checks are conducted to validate the robustness of the main results of this paper. The results of these robustness checks, not reported here, are available upon request from the authors.

To exclude the possibility that the relationship between technological and unemployment resistance is driven by extreme values in both variables, a new set of estimates are performed. First, estimates are performed excluding the first and last percentile of the dependent variable. Then, additional estimates are performed excluding the first and last percentile of the mean peak-trough ratio. The obtained results are very similar to those discussed before. Moreover, to exclude that the results are driven by invulnerable regions, i.e. regions with a positive value for the dependent variable, new estimates are performed excluding these regions. Again, the results are similar to the original estimates.

Ten regions were excluded from the original sample of regions because no technological recession phases are observed for these regions. As a robustness check, we perform new estimates including this group of ten regions, assigning a zero value to their mean peak-rough ratio and using a control dummy common to this group. The estimates results are very similar.

To measure the regions' technological resistance the authors of this paper rely on the mean value of the peak-trough ratios observed for the period 1978-2006. To control for potential biases due to possible errors in the measurement of the regions' technological resistance capacity, new estimates are performed using alternative measures, i.e. the minimum value of the peak-trough ratios, the maximum value of the peak-trough ratios and the mean value of the peak-trough ratios calculated excluding the earliest technological recession phase. These new variables are highly correlated with the original variable. The estimates results are very similar to those reported in the main text.

To control for a possible trend in the unemployment rate of a region, a set of estimates are performed including the average annual variation of the unemployment rates during the period 1999-2007. These OLS regressions consider a sub-sample of

214 regions because for 34 regions there are missing data on the unemployment rates for the period 1999-2006. Again, the results are similar to the original estimates.

Finally, we control for potential biases due to potential measurement errors in dating the starting period of the crisis. Using data on employment for European regions, a recent paper of Sensier et al. (2016) shows that the starting year of the crisis period might vary by region. The authors find that the crisis reveals its firsts effects in 2006 and the peak in the number of regions in recession is reached in 2009. In line with Sensier et al. (2006), we construct an additional measure of unemployment resistance by allowing at the crisis period to start in any year of the period 2006-2009 and to vary among regions. In particular, for each region, we identify the year t with the minimum unemployment rate during period 2006-2009 and consider the subsequent year $t+1$ as the starting year of the crisis period. Then, we calculate the unemployment resistance as the difference between the level of unemployment rate before crisis (year t) and the peak level of unemployment rate of the crisis period (from t+1 to the last period covered by our data, i.e. 2016). This alternative measure of unemployment resistance is used in additional estimates where all the independent variables are measured in the year 2004. The results of this estimates are very similar to those reported in the main text of the paper.

Appendix B: Complete table of OLS estimates for Models 3b, 7a and 7b

-Table 7 about here -

Appendix C: Table of OLS estimates for the total unemployment and for the five different categories of unemployment – Subsample of 196 European regions for which unemployment data are available for all the unemployment categories

-Table 8 about here -

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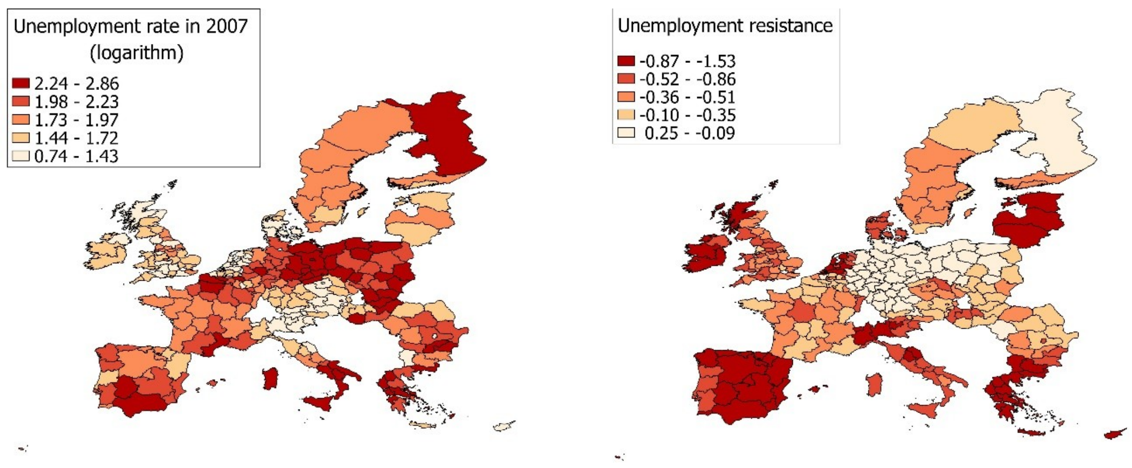

a) logarithm of regional unemployment rate in 2007 b) regional unemployment resistance for the period 2008-2016

Fig. 1 Unemployment rate in 2007 and unemployment resistance for the period 2008-2016 for the 248 NUTS2 European regions: panel a) logarithm of regional unemployment rate in 2007); and panel b) regional unemployment resistance for the period 2008-2016.

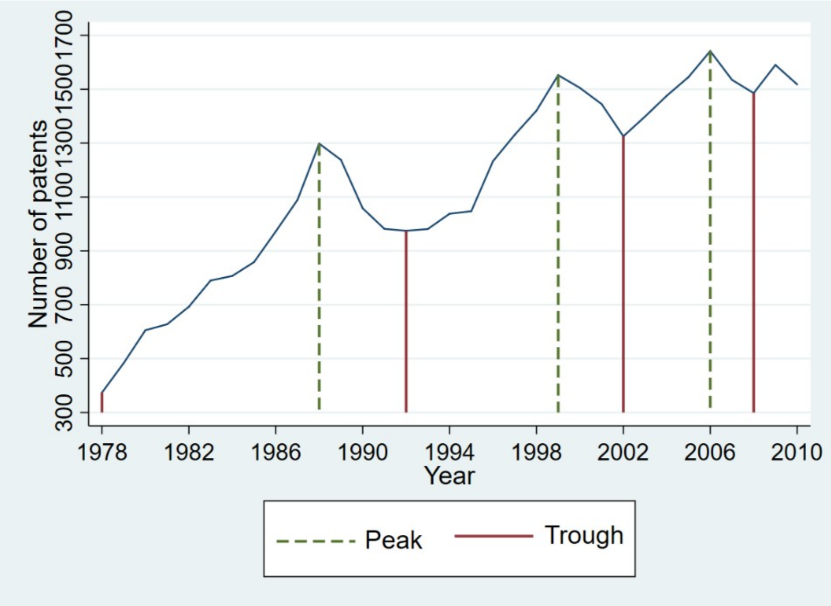

Fig. 2 Peak, trough and technological cycles for Dusseldorf (NUTS2: DEA1)

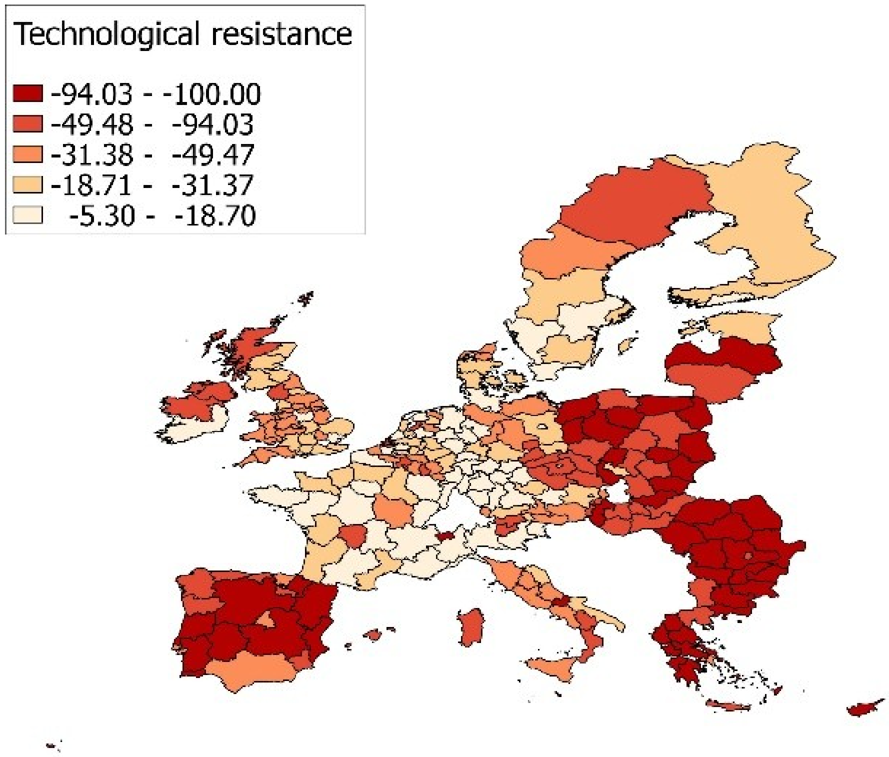

Fig. 3 Technological resistance index for the 248 NUTS2 European regions for the period 1978-2006

Table 1 Mean value of technological and unemployment resistance for five groups of regions ranked according to their levels of technological resistance

Technological resistance		Unemployment resistance
Ranking position	Mean	Mean
From 1 to 50	-13.52	-0.29
From 51 to 100	-24.11	-0.42
From 101 to 150	-40.44	-0.47
From 151 to 200	-74.33	-0.58
From 201 to 248	-99.82	-0.66
Total	-50.05	-0.49

Notes: each of the 248 European NUTS2 regions considered by our analysis is included in one of the five groups of regions based on its ranking position in terms of technological resistance level

Table 2 Mean value of unemployment resistance by group of regions with low or high level of human capital and technological resistance

		Technological resistance	
		Low	High
Human capital	Low	-0.50	-0.31
	High	-0.75	-0.41

Notes: each of the 248 European NUTS2 regions considered by our analysis is included in one of the four groups of regions based on its level of human capital and technological resistance; Low and High means respectively lower and upper median value in terms of human capital (under the rows) and technological resistance (under the columns); the result of the mean comparison t-test (not show here for the sake of clarity) performed for the two groups of regions with Low human capital and for the two groups with High human capital is significant at 1% level

Table 3 Descriptive statistics of the unstandardized variables (N=248)

Variable	Mean	SD	Min	Max
$UNEMPres_{i,2008-2016}$	-0.481	0.406	-1.528	0.254
$\log(UNEMP_{i,2007})$	1.841	0.440	0.742	2.862
$TECHres_{i,2006}$	-50.046	32.877	-100	-5.304
$HUMANcap_{i,2006}$	22.555	7.915	8.000	45.500
$RECyears_{i,2006}$	6.387	3.874	2	19
$PATpc_{i,2006}$	1.704	2.109	0.002	11.276
$HERFtech_{i,2006}$	0.071	0.106	0.008	0.611
$GDPpc_{i,2006}$	0.024	0.009	0.006	0.064
$AGRIC_{i,2006}$	0.059	0.066	0.003	0.439
$MANUF_{i,2006}$	0.194	0.069	0.058	0.388
$CONSTR_{i,2006}$	0.085	0.024	0.039	0.170
$\log(POP_{i,2006})$	7.267	0.736	4.820	9.353
$CAPITAL_{i,2006}$	0.097	0.296	0	1

Notes: country dummies are not included for the sake of clarity

Table 4 Determinants of regional unemployment resistance - OLS estimates

VARIABLES	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b
log(UNEMP$_{i,2007}$)	0.361***	0.357***	0.368***	0.372***	0.267***	0.258***
	(0.044)	(0.043)	(0.039)	(0.038)	(0.026)	(0.026)
TECHres$_{i,2006}$	0.419***	0.479***	0.212***	0.243***	0.107***	0.132***
	(0.048)	(0.048)	(0.068)	(0.066)	(0.040)	(0.040)
HUMANcap$_{i,2006}$	-0.166***	-0.172***	-0.092**	-0.103**	-0.027	-0.050
	(0.048)	(0.046)	(0.046)	(0.045)	(0.037)	(0.037)
TECHres$_{i,2006}$ * HUMANcap$_{i,2006}$		0.440***		0.304***		0.158***
		(0.092)		(0.085)		(0.048)
RECyears$_{i,2006}$			0.064	0.066	0.019	0.023
			(0.041)	(0.040)	(0.021)	(0.021)
PATpc$_{i,2006}$			0.206***	0.173***	0.010	-0.014
			(0.053)	(0.053)	(0.028)	(0.029)
HERFtech$_{i,2006}$			-0.002	-0.058	0.016	-0.010
			(0.049)	(0.051)	(0.027)	(0.028)
GDPpc$_{i,2006}$			-0.133**	-0.113*	0.131***	0.128***
			(0.063)	(0.061)	(0.043)	(0.042)
AGRIC$_{i,2006}$			-0.087	-0.096*	0.033	0.026
			(0.053)	(0.052)	(0.032)	(0.032)
MANUF$_{i,2006}$			0.137***	0.155***	0.009	0.016
			(0.047)	(0.046)	(0.028)	(0.027)
CONSTR$_{i,2006}$			-0.323***	-0.294***	-0.012	-0.013
			(0.046)	(0.046)	(0.033)	(0.032)
log(POP$_{i,2006}$)			-0.087**	-0.093**	-0.011	-0.018
			(0.044)	(0.043)	(0.026)	(0.026)
CAPITAL$_{i,2006}$			0.016	0.008	-0.109**	-0.095**
			(0.069)	(0.068)	(0.048)	(0.047)
Constant	-0.482***	-0.527***	-0.486***	-0.517***	-0.064**	-0.065**
	(0.022)	(0.022)	(0.018)	(0.020)	(0.030)	(0.030)
Country dummies	No	No	No	No	Yes	Yes
Observations	248	248	248	248	248	248
R-squared	0.329	0.387	0.597	0.618	0.931	0.934

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5 Determinants of regional unemployment resistance - OLS estimates for the subsamples of regions with lower and upper median levels of unemployment in 2007

VARIABLES	Upper median level of unemployment in 2007				Lower median level of unemployment in 2007			
	Model 4a	Model 5a	Model 6a	Model 7a	Model 4b	Model 5b	Model 6b	Model 7b
log($UNEMP_{i,2007}$)	0.510***	0.258***	0.505***	0.255***	0.336***	0.347***	0.313***	0.290***
	(0.082)	(0.043)	(0.082)	(0.044)	(0.101)	(0.059)	(0.096)	(0.057)
$TECHresi_{,2006}$	0.168**	0.029	0.193**	0.036	0.290***	0.173***	0.288***	0.197***
	(0.084)	(0.049)	(0.086)	(0.050)	(0.110)	(0.066)	(0.104)	(0.062)
$HUMANcap_{i,2006}$	0.028	0.062	0.037	0.058	-0.194***	-0.146**	-0.231***	-0.219***
	(0.066)	(0.046)	(0.066)	(0.047)	(0.068)	(0.071)	(0.065)	(0.070)
$TECHres_{i,2006}$ * $HUMANcap_{i,2006}$			0.170	0.038			0.460***	0.260***
			(0.129)	(0.067)			(0.121)	(0.075)
$RECyears_{i,2006}$	0.077	0.029	0.075	0.029	0.054	0.023	0.080	0.031
	(0.052)	(0.023)	(0.051)	(0.023)	(0.069)	(0.036)	(0.066)	(0.034)
$PATpc_{i,2006}$	0.261***	0.027	0.218**	0.016	0.229***	-0.002	0.207***	-0.011
	(0.095)	(0.045)	(0.100)	(0.050)	(0.067)	(0.041)	(0.064)	(0.039)
$HERFtech_{i,2006}$	0.041	0.055*	0.022	0.050*	0.120	-0.176*	-0.116	-0.319***
	(0.051)	(0.028)	(0.053)	(0.029)	(0.172)	(0.097)	(0.173)	(0.100)
$GDPpc_{i,2006}$	-0.238**	0.008	-0.211**	0.014	-0.072	0.323***	-0.066	0.295***
	(0.099)	(0.053)	(0.101)	(0.054)	(0.083)	(0.072)	(0.079)	(0.068)
$AGRIC_{i,2006}$	-0.154**	-0.056	-0.158**	-0.054	-0.029	0.173***	-0.040	0.144**
	(0.063)	(0.035)	(0.063)	(0.035)	(0.103)	(0.063)	(0.097)	(0.059)
$MANUF_{i,2006}$	0.184***	0.032	0.192***	0.033	0.034	-0.023	0.068	-0.005
	(0.067)	(0.036)	(0.067)	(0.036)	(0.071)	(0.044)	(0.067)	(0.042)
$CONSTR_{i,2006}$	-0.354***	-0.089**	-0.350***	-0.089**	-0.227***	0.060	-0.161**	0.071
	(0.060)	(0.039)	(0.060)	(0.039)	(0.081)	(0.060)	(0.078)	(0.056)
log($POP_{i,2006}$)	-0.029	-0.013	-0.023	-0.012	-0.125*	-0.056	-0.141**	-0.068
	(0.054)	(0.032)	(0.054)	(0.032)	(0.069)	(0.045)	(0.066)	(0.043)
$CAPITAL_{i,2006}$	0.020	-0.068	-0.017	-0.071	0.004	-0.105	0.033	-0.053
	(0.112)	(0.066)	(0.115)	(0.067)	(0.095)	(0.076)	(0.090)	(0.073)
Constant	-0.560***	-0.083**	-0.570***	-0.081**	-0.476***	-0.072	-0.552***	-0.131*
	(0.040)	(0.038)	(0.041)	(0.038)	(0.053)	(0.071)	(0.054)	(0.069)
Country dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	126	126	126	126	122	122	122	122
R-squared	0.697	0.958	0.701	0.958	0.479	0.929	0.541	0.938

Notes. standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6 Determinants of regional unemployment resistance - OLS estimates for the five different categories of unemployment

VARIABLES	Gender				Age				Long term	
	Male		Female		Young (age 15-24)		Elder (age > 24)		(> 12 months)	
	Model 8a	Model 8b	Model 9a	Model 9b	Model 10a	Model 10b	Model 11a	Model 11b	Model 12a	Model 12b
$\log(UNEMP_{i,2007})$	0.324***	0.320***	0.307***	0.302***	0.424***	0.419***	0.276***	0.269***	0.518***	0.522***
	(0.027)	(0.026)	(0.036)	(0.036)	(0.031)	(0.031)	(0.032)	(0.032)	(0.035)	(0.035)
$TECHres_{i,2006}$	0.093**	0.117***	0.066	0.083	0.108**	0.135***	0.045	0.076	0.089***	0.111***
	(0.043)	(0.043)	(0.051)	(0.053)	(0.047)	(0.049)	(0.049)	(0.051)	(0.033)	(0.034)
$HUMANcap_{i,2006}$	-0.003	-0.021	-0.047	-0.060	0.017	-0.008	0.019	-0.012	-0.031	-0.048
	(0.038)	(0.038)	(0.046)	(0.046)	(0.044)	(0.046)	(0.046)	(0.048)	(0.030)	(0.031)
$TECHres_{i,2006}$ * $HUMANcap_{i,2006}$		0.121**		0.091		0.095*		0.117**		0.098**
		(0.051)		(0.062)		(0.054)		(0.056)		(0.041)
$RECyears_{i,2006}$	-0.023	-0.020	0.016	0.018	0.013	0.016	0.024	0.027	-0.009	-0.008
	(0.022)	(0.022)	(0.026)	(0.026)	(0.023)	(0.023)	(0.024)	(0.023)	(0.018)	(0.017)
$PATpc_{i,2006}$	0.045	0.027	0.021	0.008	0.040	0.029	0.007	-0.007	0.064***	0.050**
	(0.029)	(0.030)	(0.035)	(0.036)	(0.032)	(0.032)	(0.033)	(0.033)	(0.023)	(0.023)
$HERFtech_{i,2006}$	0.022	0.003	0.020	0.005	-0.020	-0.039	0.068**	0.047	-0.012	-0.028
	(0.028)	(0.029)	(0.034)	(0.035)	(0.028)	(0.030)	(0.030)	(0.031)	(0.021)	(0.022)
$GDPpc_{i,2006}$	0.101**	0.104**	0.148***	0.150***	0.119**	0.125**	0.093*	0.100**	0.070*	0.080**
	(0.045)	(0.045)	(0.055)	(0.055)	(0.050)	(0.049)	(0.051)	(0.050)	(0.036)	(0.036)
$AGRIC_{i,2006}$	0.011	0.007	0.065	0.062	0.078**	0.076**	0.003	-0.001	0.034	0.037
	(0.033)	(0.033)	(0.040)	(0.040)	(0.034)	(0.034)	(0.035)	(0.035)	(0.026)	(0.026)
$MANUF_{i,2006}$	-0.022	-0.017	0.025	0.029	-0.042	-0.041	0.023	0.025	-0.000	0.005
	(0.030)	(0.029)	(0.034)	(0.034)	(0.032)	(0.032)	(0.033)	(0.032)	(0.022)	(0.022)
$CONSTR_{i,2006}$	-0.037	-0.032	0.007	0.011	0.023	0.024	-0.015	-0.013	0.027	0.031
	(0.035)	(0.035)	(0.042)	(0.042)	(0.040)	(0.040)	(0.041)	(0.041)	(0.028)	(0.028)
$\log(POP_{i,2006})$	-0.020	-0.028	-0.044	-0.051	0.015	0.005	0.024	0.013	-0.044**	-0.052**
	(0.028)	(0.028)	(0.034)	(0.034)	(0.030)	(0.031)	(0.032)	(0.032)	(0.022)	(0.022)
$CAPITAL_{i,2006}$	-0.112**	-0.102**	-0.060	-0.052	-0.119**	-0.111**	-0.113**	-0.103*	-0.031	-0.027
	(0.049)	(0.049)	(0.059)	(0.059)	(0.051)	(0.051)	(0.053)	(0.053)	(0.039)	(0.039)
Constant	-0.180***	-0.182***	0.020	0.019	0.029	0.018	-0.086*	-0.094**	-0.206***	-0.211***
	(0.033)	(0.032)	(0.037)	(0.037)	(0.038)	(0.039)	(0.046)	(0.045)	(0.028)	(0.028)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	238	238	238	238	207	207	207	207	219	219
R-squared	0.950	0.952	0.872	0.874	0.923	0.925	0.933	0.935	0.940	0.942

Notes: the unemployment resistance (i.e. the dependent variable) and the unemployment level in 2007 (used as control variable) are computed using data for the respective unemployment category; standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7 OLS estimates results for the total sample (Model 3b) and for the two subsamples of regions with lower (Model 7b) and upper median (Model 7a) levels of unemployment in 2007- Country dummy coefficient values are included

VARIABLES	Total sample Model 3b	Upper median level of unemployment in 2007 Model 7a	Lower median level of unemployment in 2007 Model 7b
$\log(UNEMP_{i,2007})$	0.258***	0.255***	0.290***
	(0.026)	(0.044)	(0.057)
$TECHres_{i,2006}$	0.132***	0.036	0.197***
	(0.040)	(0.050)	(0.062)
$HUMANcap_{i,2006}$	-0.050	0.058	-0.219***
	(0.037)	(0.047)	(0.070)
$TECHres_{i,2006}$ * $HUMANcap_{i,2006}$	0.158***	0.038	0.260***
	(0.048)	(0.067)	(0.075)
$RECyears_{i,2006}$	0.023	0.029	0.031
	(0.021)	(0.023)	(0.034)
$PATpc_{i,2006}$	-0.014	0.016	-0.011
	(0.029)	(0.050)	(0.039)
$HERFtech_{i,2006}$	-0.010	0.050*	-0.319***
	(0.028)	(0.029)	(0.100)
$GDPpc_{i,2006}$	0.128***	0.014	0.295***
	(0.042)	(0.054)	(0.068)
$AGRIC_{i,2006}$	0.026	-0.054	0.144**
	(0.032)	(0.035)	(0.059)
$MANUF_{i,2006}$	0.016	0.033	-0.005
	(0.027)	(0.036)	(0.042)
$CONSTR_{i,2006}$	-0.013	-0.089**	0.071
	(0.032)	(0.039)	(0.056)
$\log(POP_{i,2006})$	-0.018	-0.012	-0.068
	(0.026)	(0.032)	(0.043)
$CAPITAL_{i,2006}$	-0.095**	-0.071	-0.053
	(0.047)	(0.067)	(0.073)
AUSTRIA	-0.129**	-0.224*	-0.239***
	(0.052)	(0.113)	(0.069)
BELGIUM	-0.220***	-0.313***	-0.088
	(0.047)	(0.058)	(0.081)
BULGARIA	-0.433***	-0.571***	-0.205
	(0.088)	(0.101)	(0.158)
CYPRUS	-0.940***	-	-0.823***
	(0.135)		(0.162)
CZECH REPUBLIC	-0.236***	-0.175*	-0.258***
	(0.065)	(0.092)	(0.095)
DENMARK	-0.559***	-	-0.544***
	(0.067)		(0.082)
ESTONIA	-1.001***	-	-0.860***
	(0.139)		(0.176)
GREECE	-1.121***	-1.051***	-1.402***
	(0.059)	(0.065)	(0.140)

(continue)

Table 7 OLS estimates results for the total sample (Model 3b) and for the two subsamples of regions with lower (Model 7b) and upper median (Model 7a) levels of unemployment in 2007- Country dummy coefficient values are included (continued)

Variables	Total sample Model 3b	Upper median level of unemployment in 2007 Model 7a	Lower median level of unemployment in 2007 Model 7b
SPAIN	-1.047***	-1.016***	-0.907***
	(0.062)	(0.073)	(0.126)
FINLAND	-0.341***	-0.280***	-0.382***
	(0.074)	(0.078)	(0.140)
FRANCE	-0.403***	-0.325***	-0.506***
	(0.037)	(0.040)	(0.079)
HUNGARY	-0.368***	-0.329***	-0.355***
	(0.070)	(0.081)	(0.121)
IRELAND	-1.045***	-	-1.201***
	(0.102)		(0.131)
ITALY	-0.703***	-0.578***	-0.812***
	(0.049)	(0.066)	(0.083)
LITHUANIA	-0.996***	-	-0.836***
	(0.142)		(0.178)
LUXEMBOURG	-0.488***	-	-0.900***
	(0.142)		(0.176)
LATVIA	-0.813***	-	-0.672***
	(0.142)		(0.178)
MALTA	0.086	0.049	-
	(0.141)	(0.148)	
NETHERLANDS	-0.682***	-	-0.691***
	(0.052)		(0.075)
POLAND	-0.076	-0.123	-
	(0.066)	(0.076)	
PORTUGAL	-0.756***	-0.684***	-0.753***
	(0.075)	(0.086)	(0.163)
ROMANIA	-0.181*	-0.217*	0.088
	(0.093)	(0.118)	(0.158)
SWEDEN	-0.388***	-0.391***	-0.370***
	(0.048)	(0.056)	(0.081)
SLOVAKIA	-0.254***	-0.266***	-0.208
	(0.081)	(0.100)	(0.139)
UNITED KINGDOM	-0.400***	-0.422***	-0.318***
	(0.043)	(0.071)	(0.075)
Constant	-0.065**	-0.081**	-0.131*
	(0.030)	(0.038)	(0.069)
Observations	248	126	122
R-squared	0.934	0.958	0.938

Notes. standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8 OLS estimates for the total unemployment and for five different categories of unemployment – Subsample of 196 regions

Variable	Total unemployment		Gender				Age				Long term	
			Male		Female		Young (age 15-24)		Elder (age > 24)		(> 12 months)	
log(UNEMP$_{i,2007}$)	0.250***	0.245***	0.339***	0.335***	0.308***	0.304***	0.425***	0.420***	0.263***	0.258***	0.539***	0.543***
	(0.028)	(0.028)	(0.029)	(0.029)	(0.039)	(0.039)	(0.031)	(0.031)	(0.033)	(0.032)	(0.036)	(0.035)
TECHres$_{i,2006}$	0.076*	0.107**	0.091*	0.120**	0.073	0.093	0.118**	0.150***	0.050	0.080	0.060	0.095**
	(0.045)	(0.047)	(0.048)	(0.051)	(0.058)	(0.061)	(0.047)	(0.050)	(0.049)	(0.051)	(0.038)	(0.040)
HUMANcap$_{i,2006}$	0.031	0.001	0.060	0.033	0.022	0.001	0.017	-0.012	0.029	0.000	-0.023	-0.055
	(0.043)	(0.045)	(0.046)	(0.048)	(0.055)	(0.058)	(0.045)	(0.047)	(0.046)	(0.048)	(0.036)	(0.037)
TECHres$_{i,2006}$ * HUMANcap$_{i,2006}$		0.113**		0.101*		0.075		0.110*		0.106*		0.116***
		(0.053)		(0.057)		(0.069)		(0.056)		(0.058)		(0.044)
RECyears$_{i,2006}$	0.022	0.025	-0.009	-0.006	0.027	0.029	0.016	0.019	0.023	0.027	-0.001	0.002
	(0.022)	(0.022)	(0.024)	(0.024)	(0.029)	(0.029)	(0.024)	(0.023)	(0.024)	(0.024)	(0.019)	(0.018)
PATpc$_{i,2006}$	0.015	0.002	0.051	0.039	0.013	0.004	0.037	0.025	0.005	-0.008	0.054**	0.041
	(0.031)	(0.031)	(0.033)	(0.033)	(0.040)	(0.040)	(0.032)	(0.033)	(0.033)	(0.034)	(0.025)	(0.026)
HERFtech$_{i,2006}$	0.056**	0.037	0.048	0.030	0.039	0.027	-0.020	-0.039	0.065**	0.047	0.000	-0.020
	(0.028)	(0.029)	(0.029)	(0.031)	(0.036)	(0.037)	(0.029)	(0.030)	(0.030)	(0.031)	(0.023)	(0.024)
GDPpc$_{i,2006}$	0.082*	0.090*	0.063	0.070	0.130**	0.135**	0.119**	0.127**	0.089*	0.096*	0.076*	0.088**
	(0.048)	(0.047)	(0.051)	(0.051)	(0.061)	(0.061)	(0.050)	(0.050)	(0.051)	(0.051)	(0.040)	(0.039)
AGRIC$_{i,2006}$	-0.012	-0.010	-0.019	-0.017	0.033	0.034	0.074**	0.076**	-0.022	-0.020	0.026	0.030
	(0.034)	(0.034)	(0.037)	(0.036)	(0.044)	(0.044)	(0.036)	(0.035)	(0.037)	(0.037)	(0.028)	(0.027)
MANUF$_{i,2006}$	0.002	0.006	-0.015	-0.011	0.021	0.024	-0.043	-0.039	0.014	0.018	-0.005	0.001
	(0.031)	(0.030)	(0.033)	(0.033)	(0.039)	(0.039)	(0.033)	(0.033)	(0.033)	(0.033)	(0.025)	(0.024)
CONSTR$_{i,2006}$	-0.003	-0.004	-0.038	-0.039	0.032	0.032	0.016	0.014	-0.003	-0.004	0.010	0.010
	(0.039)	(0.038)	(0.042)	(0.041)	(0.049)	(0.049)	(0.041)	(0.041)	(0.042)	(0.042)	(0.033)	(0.032)
log(POP$_{i,2006}$)	0.001	-0.007	0.021	0.013	-0.024	-0.029	0.015	0.006	0.017	0.009	-0.012	-0.022
	(0.030)	(0.030)	(0.032)	(0.032)	(0.039)	(0.039)	(0.032)	(0.032)	(0.033)	(0.033)	(0.026)	(0.025)
CAPITAL$_{i,2006}$	-0.107**	-0.099**	-0.127**	-0.120**	-0.091	-0.086	-0.125**	-0.118**	-0.111**	-0.104*	-0.064	-0.059
	(0.049)	(0.049)	(0.053)	(0.053)	(0.063)	(0.063)	(0.052)	(0.052)	(0.053)	(0.053)	(0.042)	(0.041)
Constant	-0.060	-0.071*	-0.238***	-0.248***	0.019	0.011	0.024	0.010	-0.080*	-0.090*	-0.225***	-0.241***
	(0.041)	(0.041)	(0.044)	(0.044)	(0.051)	(0.052)	(0.039)	(0.039)	(0.046)	(0.046)	(0.036)	(0.036)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196	196	196	196	196	196	196
R-squared	0.942	0.944	0.954	0.955	0.875	0.876	0.927	0.929	0.938	0.939	0.942	0.945

Notes: the unemployment resistance (i.e. the dependent variable) and the unemployment level in 2007 (used as control variable) are computed using data for the respective unemployment category; standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1