Papers in Evolutionary Economic Geography

16.08

Resilience in the European Union: the effect of the 2008 crisis on the ability of regions in Europe to develop new industrial specializations

Jing Xiao, Ron Boschma, Martin Andersson

Utrecht University
Urban & Regional research centre Utrecht

Resilience in the European Union: the effect of the 2008 crisis on the ability of regions in Europe to develop new industrial specializations

Jing Xiao*, Ron Boschma*# and Martin Andersson*$

* Center for Innovation, Research and Competence in the Learning Economy (CIRCLE), Lund University, PO Box 117, SE-22100 Lund, Sweden. (Email: jing.xiao@circle.lu.se)

Urban and Regional Research Centre Utrecht (URU), Utrecht University, PO Box 80 115, NL-3508 TC Utrecht, the Netherlands. (Email: r.boschma@geo.uu.nl)

$ Department of Industrial Economics, Blekinge Institute of Technology, 371 79 Karlskrona, Sweden. (Email: martin.andersson@bth.se)

15 April 2016

Abstract

This paper adopts an evolutionary framework to the study of industrial resilience. We present a study on European regions and assess the extent to which the capacity of their economies to develop new industrial specializations is affected by the global economic crisis of 2008. We compare levels of industry entry in European regions in the period 2004-2008 and 2008-2012, i.e. before and after a major economic disturbance. Resilient regions are defined as regions that show high entry levels or even increase their entry levels after the shock. Industrial relatedness and population density exhibit a positive effect on regional resilience, especially on the entry of knowledge-intensive industries after the shock, while related variety per se shows no effect on regions being resilient or not.

Key words: regional resilience, evolutionary economic geography, new growth paths, related variety, industrial relatedness

JEL: B52 O18 R11

1. Introduction

Resilience is higher on the scientific and political agenda than ever before. Due to globalization, regions as well as nations have become more exposed to external events, and have been confronted with a number of major global disturbances like the economic crisis of 2008 and environmental risks due to climate change. There is an expanding number of studies that investigates the responsiveness of economies to absorb such major shocks. They tend to reveal that resilience between countries and regions differ widely. At the same time, concerns have been raised about the precise meaning of resilience, its definition and conceptualization, the appropriate framework to analyze regional resilience, and its main determinants (Christopherson et al. 2010; Hassink 2010; Martin and Sunley 2015; Capello et al. 2015).

This paper has three objectives. First, we present an evolutionary framework to resilience which focuses on the impact of shocks on the capacity of an economy to diversify and develop new industrial specializations. Such industrial resilience is regarded a key element of long-term economic development. This follows the evolutionary framework proposed by Boschma (2015), where the main argument is that resilience should integrate the capacity of an economy to recover from shocks with its capacity to develop new growth paths after a shock. Second, we apply this evolutionary framework to a study on the resilience of European regions by focusing on their capacity to develop new industrial specializations when confronted with the global economic crisis of 2008. This evolutionary focus makes our paper complementary to other studies on resilience of European countries and regions (Davies 2011; Groot et al. 2011; Capello et al. 2015). We assess the extent to which the ability of European regions to enter new industrial specializations has been affected by the 2008 crisis. Resilient regions are defined as regions that show high entry levels or even increase their entry levels after the shock. Third, we make an attempt to explain why some European regions show resilience, while others do not. We show that industrial relatedness among economic activities in a local economy and population density exhibit a positive effect on regions being resilient or not, while related variety shows no effect.

The structure of the paper is as follows. The next section outlines the literature on regional resilience, and explains how the evolutionary approach differs from other resilience frameworks. Then, we discuss the data, the variables and the methodology, after which we present the main findings. The last section concludes.

2. Industrial resilience: an evolutionary framework in a regional context

Recently, scholars show a strong interest in the topic of industrial resilience, although this interest is not new (Christopherson et al. 2010). There is a rapidly expanding number of empirical studies that investigates the responsiveness of countries and regions to absorb major shocks, such as the financial crisis (e.g. Groot et al. 2011; Martin et al. 2014) or natural disasters, like the flooding of cities (Kocornik-Mina et al. 2016). In these studies, resilience is defined as the ability of countries or regions to withstand shocks as well as their ability to recover from them. These studies show that countries and regions differ widely in their vulnerability to shocks, and in their capacity to overcome shocks and bounce back.

This interest has initiated a debate about the usefulness of the resilience concept and its added-value to our understanding of economic development (see e.g. Hassink 2010; Pike et al. 2010). Concerns have been raised about resilience being a fuzzy concept and the lack of agreement on a definition of resilience (Pendall et al. 2010; Martin 2012). There has been an ongoing search for the appropriate theoretical and conceptual framework to analyze resilience. Some scholars have advocated an engineering-based concept of resilience that is popular in mainstream neo-classical economics (Rose 2004; Fingleton et al. 2012). In this equilibrium framework, resilience is defined as the ability of an economy to resume its stable equilibrium state after a shock, or its ability to return to its pre-existing equilibrium state. In the context of regions, this implies for example that the most resilient region is a region that does not undergo any economic change at all, even in the event of major shocks. This view has been criticized for making no reference to the need of structural change for long-term economic development (Simmie and Martin 2010).

Other scholars have adopted an ecological-based concept of resilience in a multi-equilibria setting (Reggiani et al. 2002; Martin 2012; Zolli and Healy 2012). Ecological resilience is defined as the magnitude of a shock that an economy can withstand without moving to a new equilibrium state, or as the ability of an economy to shift from an inferior to a superior long-run equilibrium growth path. The first case comes close to the concept of engineering resilience, where the most resilient region is the one that can accommodate even extreme shocks without adapting or making any important transitions. The second case is more dynamic, as a resilient economy adapts and transforms itself successfully in response to a shock, in contrast to an economy that remains locked-in into an obsolete or dysfunctional structure. However, this ecological approach to resilience only indirectly measures the importance of structural change (as observed in a new superior equilibrium growth path) as in Martin (2012) and Fingleton et al. (2012), but does not provide evidence what structural change has occurred, what were its underlying determinants, and why different regions or nations show different degrees of resilience. This ecological framework remains stuck in an equilibrium setting in which the process of resilience remains a black box (Swanstrom 2008; Bristow and Healy 2014).

More recently, scholars have pleaded for an evolutionary approach to resilience, to leave behind the equilibrium framework (Christopherson et al. 2010; Pike et al. 2010; Simmie and Martin 2010; Boschma 2015; Martin and Sunley 2015). The evolutionary take on resilience defines resilience as the ability of an economy to cope with the Schumpeterian process of creative destruction, and more in particular, its ability to diversify successfully and to develop new growth paths that is considered essential to offset inevitable processes of decline (Saviotti and Pyka 2004). It is misleading to consider an economy as resilient when it withstands structural change, because it is exactly this lack of adaptive capacity that would be detrimental to its long-term economic development. Instead, an economy is considered resilient when it manages to embrace structural change and enable new growth paths to develop, because it is this capacity that is crucial for its long-term economic development.

In the context of regions, the evolutionary approach focuses on the question what makes a region more successful in developing new growth paths. There are various evolutionary strands (Boschma and Martin 2010) from which the resilience literature draws inspiration (Simmie and Martin 2010). What evolutionary scholars tend to share is that they often observe conflicting tendencies in regions that affect their resilience. In the path dependence literature (Hassink 2005; Martin and Sunley 2006; Pike et al. 2010), this is embodied in the distinction between adaptation and adaptability, after Grabher (1993). Adaptation refers to the adaptive capacity of regions within their own strong specializations and established paths. This so-called 'positive lock-in' brings benefits to a region in terms of positive local externalities, but is perceived to undermine the 'adaptability' of a region simultaneously: the prime focus on adaptation and reproduction of existing local structures would negatively affect the ability of regions to develop new pathways. This 'negative lock-in' may arise due to a lack of potential local sources of recombinations, but also because of myopia, inward-looking local networks, institutional lock-in, and sunk costs (Boschma and Lambooy 1999).

Evolutionary approaches make an effort to explore how this tension or conflict may be solved, so as to increase the adaptability of regions, and thus their resilience (Boschma 2015). Simmie and Martin (2010) has followed the ecological model of adaptive cycle by Pendall et al. (2008), also known as 'panarchy' that provides a dynamic framework in which regions can move out of a state of low resilience, but also includes the possibility that regions can fall back again. However, as Simmie and Martin (2010) admit themselves, this model remains overly descriptive and lacks a guiding framework that explains which the determinants of regional resilience are and why a region is capable of shifting from one phase to the next.

Boschma (2015) proposed an evolutionary framework that explores which determinants of regional resilience can overcome the trade-off between adaptation and adaptability, so as to enhance the resilience of regions in terms of their capacity to develop new growth paths. This framework focuses attention on the structure of the regional knowledge base. Diversified regions are perceived to better accommodate sector-specific shocks (Essletzbichler 2007), especially when their local industries share similar skill requirements (Neffke and Henning 2013; Diodato and Weterings 2015). This is because redundant employees are expected to find jobs more easily in local industries that are skill-related to the sector that was negatively affected by a shock (Holm et al. 2014; Eriksson et al. 2015; Nyström 2015).

But apart from this regional labor matching effect of related variety, diversified regions may also have more potential to make new recombinations across local industries out of which new growth paths can develop, also known as 'Jacobs' externalities'. Again, this might especially apply to regions with related variety, as recombinations are more feasible and can be made more effective across activities that share similar knowledge and skills (Frenken et al. 2007). Indeed, recent studies (Neffke et al. 2011; Boschma et al. 2013) have shown that regions diversify into activities that are related to existing local activities, in which local capabilities are rejuvenated and redeployed in new combinations. So, related variety may not only enhance the ability of regions to absorb shocks (Balland et al. 2015; Diodato and Weterings 2015) but also boost their ability to develop new growth paths. Balland et al. (2015) demonstrated that U.S. cities with knowledge bases that have a high degree of relatedness to the set of existing technologies in which cities do not yet possess comparative advantage had a greater capacity to withstand technological crises, and a higher tendency to limit the intensity and duration of these crisis events. They referred to this potential of cities to reconfigure their local technological assets as technological flexibility.

This does not preclude the possibility that regions with unrelated variety may also facilitate the development of new growth paths. On the contrary, though a rarer event, regions are engaged in unrelated diversification now and then (Neffke et al. 2011). Castaldi et al. (2015) found that unrelated variety enhanced the possibility of US regions to introduce major technological breakthroughs (so-called super patents), because such regions may offer better opportunities to make new combinations between unrelated technologies.

3. Data

Our study analyses the following basic questions: to what extent has the global economic crisis of 2008 affected the capacity of European regions to develop new industry specializations after this shock, to what extent do European regions differ in this respect, and to what extent can related variety and unrelated variety of regions' industrial base, among other factors, explain this diverging pattern of resilience of European regions?

From 2008 to 2010, a deep economic crisis swept over Europe. Figure 1 shows quarterly percentage change of GDP per capita from 2000 to 2012 for EU-28 and EU-15 countries. The crisis mainly concentrated in the period starting in the third quarter of 2008 until the first quarter of 2010. During this period, European countries experienced a persistent negative percentage change of GDP per capita.

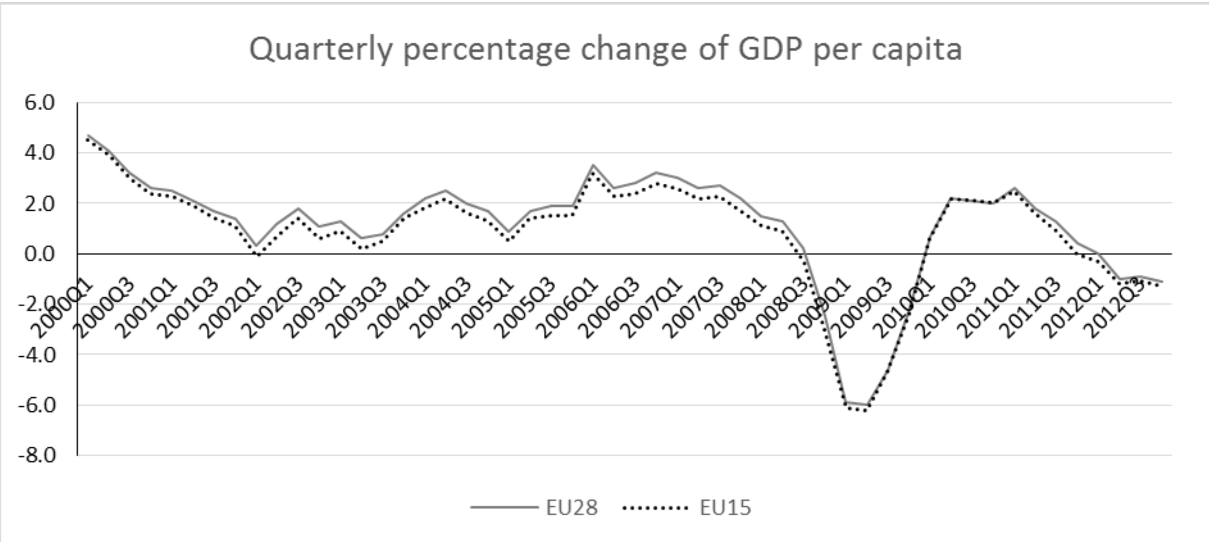

Figure 1 Quarterly percentage change of GDP per capita from 2000 to 2012

To study resilience of European regions, we use employment data from the Orbis database, compiled by Bureau Van Dijk, covering the period 2004 to 2012. The dataset has been substantially processed[1] by summarizing employment into 173 NUTS2 regions (using the 2010 classification) in 12 European countries and 323 tradable NACE2 (version 2) 4-digit sectors.[2] The 12 countries cover all main parts of the European Union: western and northern Europe (Belgium, Germany, France, the Netherlands and Denmark), eastern Europe (Bulgaria, Poland and Romania) and southern Europe (Spain, Greece, Italy and Portugal).[3]

Among the 323 sectors, there are 222 manufacturing sectors, 35 service sectors and 66 other sectors.[4] Based on the OECD industry classification (Hatzichronoglou 1997; Eurostat 2015), we make a distinction between High Knowledge-Intensive (HKI) industries (high-tech and medium-high-tech manufacturing sectors and knowledge-intensive services) and Low Knowledge-Intensive (LKI) industries (medium-low-tech and low-tech manufacturing sectors and less knowledge-intensive services) because European regions might differ in their ability to create new high knowledge-intensive versus low knowledge-intensive industries. Moreover, determinants of regional resilience might differ between the two types of sectors, as related variety might matter more for the creation of new knowledge-intensive industries (Hartog et al. 2012). Our dataset contains 92 HKI-sectors and 165 LKI-sectors.

4. Entry of new industries in European regions before and after the crisis

As discussed before, the regional resilience literature should not take for granted structural change and only observe it indirectly through new equilibrium regional growth paths, but make structural change part of the definition of regional resilience and measure it directly through the ability of regions to develop new industries. So, a successful response to a shock by a region (high resilience) is its ability to restructure and reorient its regional resources (capital, labor, knowledge, institutions, networks etc.) and move its regional economy into related or entirely new paths of development. Accordingly, we compare the levels of entry of

[1] See Cortinovis and Van Oort (2015) for more details in terms of construction of the dataset.

[2] Compared with the original dataset, the dataset used in this paper has been adjusted in two respects. One is that we drop some countries either because the countries are severely affected by missing values in employment in the Orbis dataset or because the countries have one NUTS2 region only, and so no variation within these countries can be captured with the data.

[3] We divide countries into western, eastern, northern and southern European countries in accordance to the typology by the United Nations Statistics Division.

[4] Other sectors are defined by NACE2 code 01-03, 05-09, 35-39 and 41-43.

new industries in regions before and after the crisis. For that reason, we divide our data into two 4-year periods: a pre-recession period (2004-2008) and a period during and after the recession (2008-2012).

We identify the entry of a new industry in a region when that region becomes specialized in that industry. This is gauged by a location quotient (LQ) index which measures the level of industrial composition for each region relative to the overall level of industrial composition in the EU. However, there is no consensus in the literature about the cut-off value of the LQ index in terms of delimiting industrial agglomeration (O'Donoghue and Gleave 2004). Given this problem, we use a bootstrap method, developed by Tian (2013), to identify a statistically significant cut-off value of standardized LQ for each industry.[5] Moreover, we account for the absolute employment growth for each sector-region combination and include it as an additional criterion to identify specialized industries.[6] This is to ensure that the entry of a new specialized industry in a region is accompanied with absolute employment growth of that industry in the region. So, we observe an entry of a new industry if the industry is found to be specialized by region c at year t but not at year t-4, that is, the standardized LQ of this industry in region c is higher than the significant cut-off value for this industry at year t, and region c has a positive employment growth in this sector during between t and t-4. Then, we sum the number of new specialized industries for each region and for each period, repetitively.

One source of bias with this methodology is that entry numbers may be positively related to the market size of regions. In order to test this, we calculate the correlations between entry numbers and levels of GDP or employment (in logarithmic forms).[7] As shown in Table 1, we do not find systematic positive correlations between entry numbers and levels of GDP or employment.

[5] For the detailed procedures in using the bootstrap method to identify the cut-off value of standardized LQ for each industry, see Cortinovis et al. (2016).

[6] The average growth rates are calculated for each time interval based on employment data from Orbis.

[7] GDP and employment are measured at the beginning year of each time interval.

Table 1 Correlations between entry numbers and levels of GDP or employment

Variables	2004-2008		2008-2012	
	GDP (log)	Emp (log)	GDP (log)	Emp (log)
All sectors	0.0491	0.1525*	-0.1490*	-0.0445
	[0.5211]	[0.0513]	[0.0505]	[0.5610]
HKI sectors	0.1602**	0.1793**	0.0897	0.0933
	[0.0353]	[0.0216]	[0.2403]	[0.2221]
LKI sectors	0.0032	0.0291	-0.1401*	-0.0361
	[0.9666]	[0.7114]	[0.0660]	[0.6371]

Note: Significance level in square brackets. *** p<0.01, ** p<0.05, * p<0.1. Data source: Cambridge Econometrics regional database and Eurostat regional database.

Figure 2 shows the entry numbers of new specialized industries (all sectors) of the 173 NUTS2 European regions for the period of 2004-2008 (the left graph) and the period of 2008-2012 (the right graph), respectively. The entry numbers of specialized industries ranges from 0 to 9 during the period 2004-2008. The top three regions in terms of number of new specialized industries are Veneto in Italy (9 industries), Dresden in Germany (6 industries) and Antwerp in Belgium (6 industries). During the period of 2008-2012, the number ranges from 0 to 7. The top three regions in terms of number of new specialized industries during 2004-2008 are East Macedonia and Thrace in Greece (7 industries), North Holland in the Netherlands (6 industries) and Vest in Romania (5 industries).

The employment of newly specialized sectors that enter during 2004-2008 account for about 1.9% of total employment in all sectors in all regions in 2004, while the employment of newly specialized sectors that enter during 2008-2012 account for about 1.5% of total employment in all sectors in all regions in 2008. However, the annual average growth rate of newly specialized sectors is 29% for the period of 2004-2008 and 17% for the period of 2008-2012. By contrast, the annual average growth rate of the total employment in all sectors in all regions was 2.2% from 2004 to 2008, and -0.2% from 2008 to 2012.

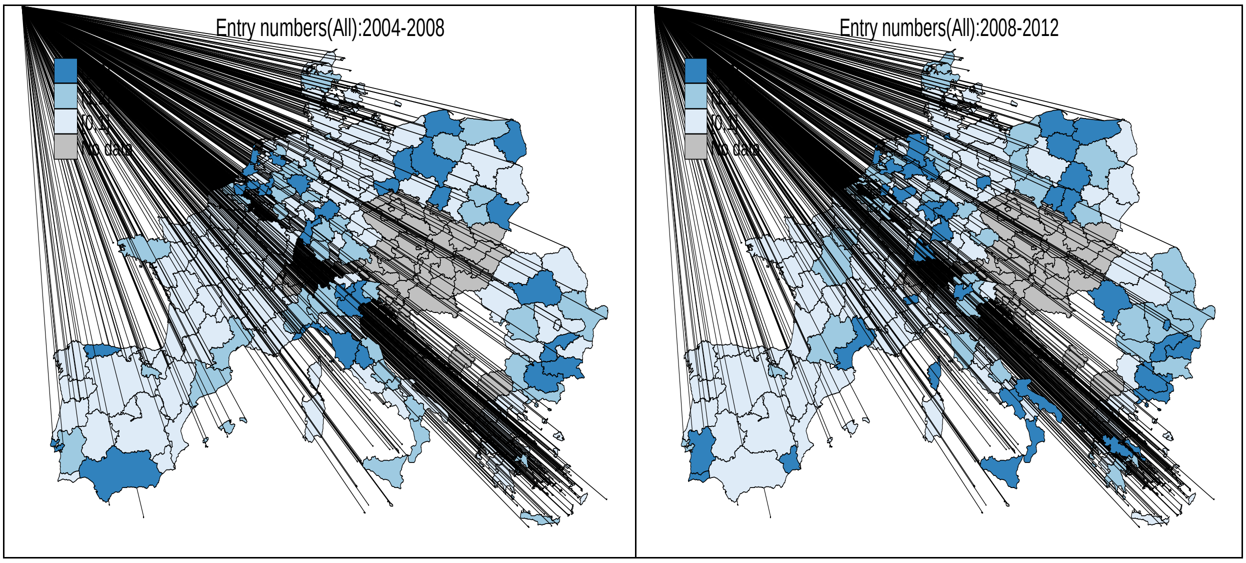

Figure 2 Entry numbers of new specialized industries in European regions

Table 2 reports average entry numbers of new specialized industries (all, HKI and LKI sectors) by country groups. The effect of the 2008-2010 crisis is clearly noticeable for HKI sectors of all country groups: the average entry level of new specializations in regions in higher before the crisis than during and after the crisis for HKI sectors. During the period of 2004-2008, it is noteworthy that regions in eastern European countries have the highest level of average entry numbers when it comes to all and LKI sectors. By contrast, the differences in average entry numbers between western and northern European countries and southern European countries are quite marginal in all and LKI sectors. However, in HKI sectors, the difference in average entry numbers between western and northern European countries and eastern European countries is very small but the average numbers for the two country groups are both higher than that for southern European counties. During the period of 2008-2012, the pattern changes slightly in HKI sectors, where regions in western and northern European countries have the highest level of average entry numbers although the difference in entry numbers are small between western and northern European countries and eastern European countries. A preliminary impression is that regions in western and northern European countries seem to more resilient in terms of creating new HKI sectors, while regions in eastern European countries seem to be more resilient in terms of creating new LKI sectors.

Table 2 Average entry numbers of new specialized industries by country groups

	2004-2008			2008-2012		
	West+north	East	South	West+north	East	South
All sectors	1.34	2.00	1.36	1.39	2.27	1.40
HKI sectors	0.60	0.67	0.42	0.55	0.50	0.27
LKI sectors	0.64	0.80	0.67	0.59	1.33	0.65

5. Resilience of European regions

We employ transition probability analysis to identify resilient regions. First, we rank regions based on three quantiles of entry numbers for each time interval. Second, we divide the regions as high, medium and low groups based on their ranks. Third, we construct a transition probability matrix where each element represents the probability of transiting from group m to group n between the period of 2004-2008 and the period of 2008-2012, see Equation (1).

$$p_{mn} = P(g_{2004-2008} = m | g_{2008-2012} = n) \quad (1)$$

Moreover, we normalize the probability by the frequency of regions of each column. In this way, the normalized probability represents a transition probability relative to the share of regions of each rank group during the period of 2008-2012. Table 3 reports the transition probability matrix. The first and last cells in the diagonal of each panel represents regions with persistently low and high entry numbers respectively. In the panel of all sectors, it is noteworthy that all diagonal values are higher than 1. That is to say, regions show a persistent pattern in terms of entry numbers of all sectors. Moreover, we find higher probabilities (larger than 1) from medium to high or from high to medium relative to that from low to medium/high. This implies that the transition between medium and high are relatively easy than that between low to medium/high in all sectors.

Table 3 Transition probability matrix of entry numbers: 2004-2008 and 2008-2012

All sectors		2008-2012		
		Low	Medium	High
2004-2008	Low	1.12	0.92	0.77
	Medium	0.79	1.16	1.37
	High	0.87	1.04	1.29

HKI sectors		2008-2012		
		Low	Medium	High
2004-2008	Low	1.06	1.01	0.60
	Medium	1.01	1.05	0.80
	High	0.68	0.82	3.56

LKI sectors		2008-2012		
		Low	Medium	High
2004-2008	Low	0.91	1.12	1.05
	Medium	1.11	0.76	1.15
	High	1.11	1.05	0.51

In the panel of HKI sectors, we also find that the diagonal probabilities are all higher than 1. Especially, the last cell in the diagonal exhibits a strikingly high level of probability than that other cells in the diagonal, which means entry numbers of HKI sectors are particularly persistent in the high rank group compared to the low/medium rank group. By contrast, compared to all sectors, we find higher probabilities (larger than 1) from low to medium or from medium to low relative to that from high to low/medium. This implies that the transition between low and medium is relatively easy than that between high to low/medium in HKI sectors. In the panel of LKI sectors, we find the diagonal probabilities are all lower than 1. By contrast, all probabilities in the off-diagonal are high than 1. That is to say, there is no persistent pattern in terms of entry numbers of LKI sectors. From the transition probability analysis, we find a generally persistent pattern in terms of entry numbers if we pull all sectors together. But if we distinguish sectors by industry groups, we find that the persistent pattern of entry numbers mainly pertains to HKI sectors.

Based on the transition probability analysis, we define resilient regions as those that remain in the high rank group and those that transit from the low rank group before the recession (2004-2008) to the high rank group during and after the recession (2008-2012). By contrast, non-resilient regions are defined as those that remain in the low rank group or those that transit from the high rank group before the recession to the low rank group during and after the recession. A residual group of regions does not belong to the category of resilient regions and the category of non-resilient regions. Figure 3 displays the geography of resilience: it shows maps of resilient and non-resilient regions based on the dynamics of their entry levels before and after the crisis for all sectors, for the HKI sectors and for the LKI sectors, respectively.

For all sectors, we identify 25 resilient regions and 78 non-resilient regions. The resilient regions consist of 8 regions that remain in the high rank group and 17 regions that transit from the low rank group to the high rank group, such as Limburg in Belgium, Severen tsentralen in Bulgaria, Unterfranken in Germany, Provincia Autonoma di Trento in Italy, Noord-Holland in the Netherlands, Sterea Ellada in Greece, Región de Murcia in Spain and Corse in France. For HKI sectors, there are 13 resilient regions and 80 non-resilient regions. The resilient regions include 7 regions that remain in the high rank group and 6 regions that transit from the low rank group to the high rank group, such as Limburg in Belgium, Stuttgart in Germany, Veneto in Italy, Noord-Holland in the Netherlands, Severen tsentralen in Bulgaria, Corse in France and Śląskie in Poland. For LKI sectors, we identify 17 resilient regions and 60 non-resilient regions. The resilient regions include 2 regions that remain in the high rank group and 15 regions that transit from the low rank group to the high rank group, such as Freiburg in Germany, Ionia Nisia in Greece, Región de Murcia in Spain, Provincia Autonoma di Trento in Italy, Gelderland in the Netherlands, and Nord-Est in Romania.

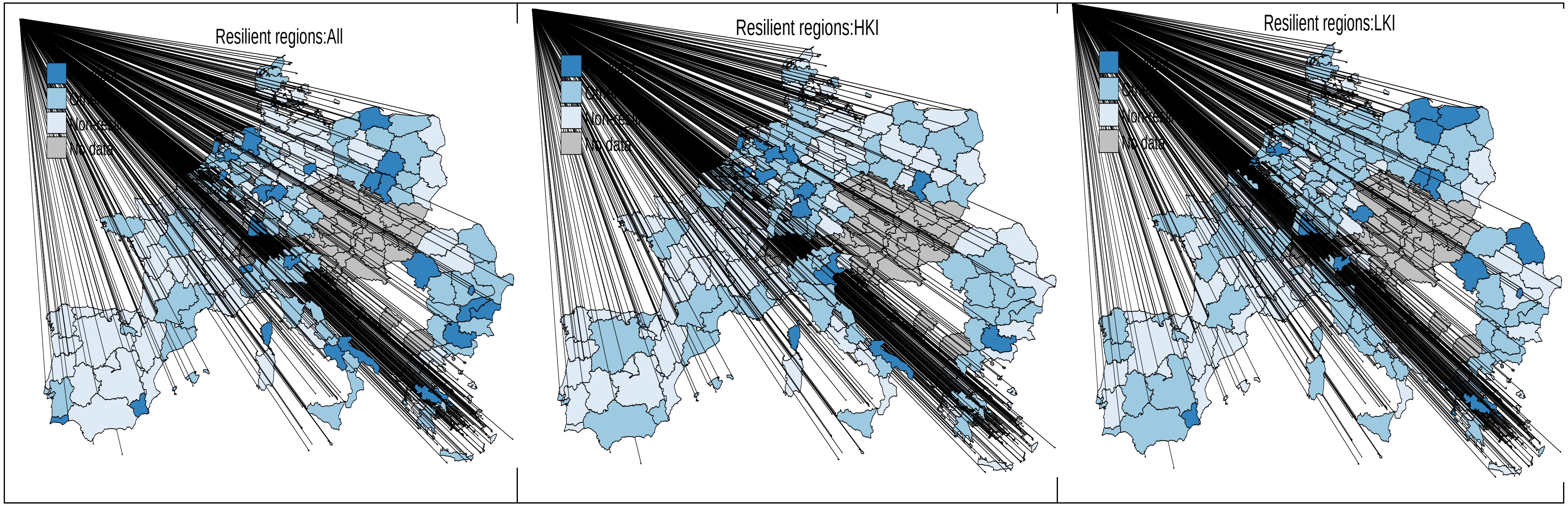

Figure 3 Resilient and non-resilient regions

6. Econometric analysis

The previous section shows that there is a divergent pattern of industrial resilience across European regions. This section aims to what factors that explains whether a region show resilience. To this end, we estimate the influence that a number of theoretically motivated regional characteristics, in particular related and unrelated variety, have on the probability that a region develops new industry specializations.

6.1 Variables and empirical model

To calculate related and unrelated variety, we use an entropy measure, based on employment data of 323 sectors in 173 NUTS2 regions. Frenken et al (2007) computed unrelated variety as the diversity across 2-digit Standard Industrial Classification groups, while related variety was measured as the weighted sum of 5-digit variety within each 2-digit group. In our analysis, however, sectoral division is according to NACE aggregation scheme (version 2). As pointed out by Cortinovis and Van Oort (2015), the use of sections as a boundary to distinguish between sector variety and within sector variety can better capture the relatedness among 2-digit sectors in the NACE aggregation scheme. Therefore, we calculate unrelated variety as the variety across sections while related variety as the weighted sum of 4-digit diversity within each section, as in Equations (2), (3a) and (3b). We have a total of 323 4-digit NACE sectors that are grouped into 13 sections.

$$UV = \sum_{s=1}^{S} P_s \, log_2(\frac{1}{p_s}) \tag{2}$$

$$RV = \sum_{s=1}^{S} P_s \, H_s \tag{3a}$$

$$H_s = \sum_{i \in s} \frac{P_i}{P_s} \, log_2 \, (\frac{1}{P_i/P_s}) \tag{3b}$$

where *UV* refers to unrelated variety; *RV* refers to related variety; the subscript *s* denotes a section *S*; the subscript *i* refers to a 4-digit sector that exclusively belongs to one section; *P* refers to employment share; and H_s denotes the 4-digit variety within each section *S*.

We also construct a variable aimed to reflect the potential of reconfiguration of local industrial assets. Put differently, we want a variable that describes the ease with which a region can adapt its industrial portfolio in the event of shocks. Following Balland et al (2015), we develop such a variable by combining a measure of relatedness with information on the industrial portfolio of a region. We call this measure industrial relatedness. To measure relatedness between pairs of industries, we employ co-occurrence analysis to construct an industry proximity matrix. This method has been developed by Hidalgo et al. (2007) with the basic assumption that the more related two products are, the more likely that the two products are produced in the same location. We measure industry proximity by examining the probability of co-specialization of two industries in the same region. Doing so, we obtain a 323-by-323 matrix that reflects industrial relatedness in the 173 European regions. Industrial relatedness in each region is calculated as the average relatedness or proximity of all industries that are specialized in region c to all the industries that are present but have not been specialized in region c,[8] as in equation (4):

$$ind\_related_c = \sum_i [\left(\frac{\sum_j \varphi_{i,j}\, y_{j,c}}{\sum_j \varphi_{i,j}}\right) x_{i,c}] \,/ \sum i \qquad (4)$$

where $\varphi_{i,j}$ is the proximity index between industries i and j, $y_{j,c}$ is a dummy variable, equaling to 1 if industry j is present but not specialized in region c, and $x_{i,c}$ is a dummy variable, equal to 1 if industry i is specialized in region c.

To control for regional heterogeneity, we include a set of control variables that are regarded to be important determinants of regional diversification or growth: localization economies, population density (indicator of urbanization economies), average growth rate of Gross Domestic Product (GDP) per capita, GDP level, share of workers in science and technology (S&T) in active population, level of gross capital formation per thousand employees, and quality of government. Localization economies has been measured by means of the Los-index (Los 2000). As emphasized by Frenken et al. (2007), the Los-index not only considers the absolute scale (number of employment) of industries clustered in a region but also addresses the technological relatedness among the industries, making it a better indicator than conventional specialization indicators. Los (2000) based the technological relatedness matrix on a national input and output table. In our analysis, however, we use the proximity index φ to indicate the technological relatedness for each pair of industries. A higher Los-index means a

[8] Compared to the method by Balland et al. (2015), we construct industrial relatedness with some adjustments due to the characteristics of our dataset.

higher level of concentration of one or several technologically-related sectors in a region. The mathematical notation of the Los-index is shown in Equation (5):

$$Los_c = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(E_{i,c}*E_{j,c}*\varphi_{i,j})}{\sum_{i=1}^{n}\sum_{j=1}^{n}(E_{i,c},*E_{j,c})} \tag{5}$$

The average growth rate of GDP per capita in a 4-year interval is computed as the average log difference of GDP per capita in the period 2004-2008. Population density, level of GDP, shares of workers in S&T in active population and gross capital formation per thousand employees are all in logarithmic form. We use the European Quality of Government Index (EQI) 2010 data as a proxy of quality of government for 2004, by assuming that formal institutions change slowly. The EQI data for Belgium, Germany and Greece are only available at the NUTS1 level. EQI are obtained from the website of The Quality of Government Institute at University of Gothenburg (Charron et al., 2013; 2014). The other data are derived from Cambridge Econometrics regional database and Eurostat regional database. Except for EQI and average growth rates of GDP per capita, all independent variables are measured at 2004. Descriptive and summary statistics are displayed in Table A1 [9] and correlation coefficients in Table A2 in the appendix.

To assess the influence that our variables have on the likelihood that a region is resilient, we estimate Logit regressions at the regional level. The benchmark model is shown in Equation (6):

$$Resi_c = \beta_1 * ind\_related_c + \beta_2 * rv_c + \beta_3 * uv_c + \gamma * Con_c + \varepsilon_{c,p} \tag{6}$$

where the subscript c refers to region c; $Resi_c$ is a dummy variable that identifies resilient regions, equaling to 1 if the region belongs to resilient regions and 0 otherwise (including both non-resilient regions and other regions); $ind\_related_c$ is an indicator of industrial relatedness in region c; rv_c measures related variety in region c; uv_c measures unrelated variety in region c; Con_c is a vector of control variables at regional level in region c; and $\varepsilon_{c,t}$ is the error term.

[9] There are missing values in some control variables.

6.2 Results

All continuous regressors are standardized before they enter estimation. We conduct the estimation for all sectors, HKI sectors and LKI sectors and report the results separately in Tables 4, 5 and 6. In each table, we distinguish between resilient regions that remain in the high rank group (Class A) and those that transit from the low rank group to the high rank group (Class B). In the first panel of each table, we take resilient regions from both Class A and Class B. In the second panel, we take resilient regions only from Class A. In the third panel, we take resilient regions from Class B only. In each panel, Specification (1) only includes industrial relatedness. Specification (2) adds all the other variables. As some variables may suffer from multi-collinearity problems (see Table A2), Specification (3) includes only main predictors and variables with significant coefficients in Specification (2).

In Table 4, if we take resilient regions as those from both Class A and Class B, we find that industrial relatedness only has a significant coefficient (10% significance level) in Specification (3). If we take resilient regions from Class A only, we find that industrial relatedness has a significant effect in both Specification (2) and (3). In other words, when the average relatedness to new industries in a region increases, the higher the capacity of a region to maintain high industry entry levels during and after the shock. In this panel, we also find that population density, level of GDP, share of workers in S&T in active population and EQI exhibit significant effects on being resilient regions. More specifically, population density, share of workers in S&T and EQI show positive effects whereas level of GDP has a negative effect on regional resilience. In Specification (3), however, the share of workers in S&T is not significant. If we take resilient regions from Class B, industrial relatedness is not found to have a statistically significant effect in any of the three specifications.

In Table 5, in both the first and third panel, we find no significant effect of industrial relatedness on being resilient in any of the three specifications. By contrast, in the second panel where we take resilient regions from Class A, we find that industrial relatedness has a significant effect in all three specifications. In this panel, we also find that unrelated variety, average GDP growth rate, population density, gross capital formation per thousand employees and EQI exhibit significant effects on regional resilience in Specification (2). More specifically, unrelated variety, average GDP growth rate and gross capital formation exhibit negative effects whereas population density and EQI have positive effects on being a resilient region. In Specification (3), average GDP growth rate, gross capital formation and EQI are not significant anymore.

In Table 6, we do not find that industrial relatedness has a significant effect on being resilient regions in any specifications and panels. However, it is noteworthy that average GDP growth rate exhibits a significantly positive effect on regional resilience in both Specification (2) and (3) for all panels. Moreover, the coefficients of average GDP growth rate are much higher for resilient regions from Class A than resilient regions from Class B.

7. Robustness check

To check whether our main findings are sensitive to different estimators, we re-conduct estimation of the second panels (Panel Class A) for all sectors and HKI sectors, respectively, based on probit and OLS models separately, see Table A3. The results exhibit a similar pattern with our main findings. The main difference is that the results based on OLS model reveal that industrial relatedness is not significant in Specification (2) for HKI sectors.

A typical concern with spatial data analysis is whether the estimations suffer from spatial autocorrelation. To check this, we test for potential spatial autocorrelation based on the spatial error and lag model, respectively. The results are reported in Table A4 in the appendix. It is clear from Table A4 that all tests show that our results from Panel Class A for all sectors do not suffer from the problem from spatial autocorrelation. In Specification (1) in Panel Class A for HKI sectors, three (Moran's I test and Robust Lagrange multiplier test in spatial error model and Robust Lagrange multiplier test in spatial lag model) out of five tests show the results suffer from the problem from spatial autocorrelation. The explanation could be that we did not include any control variables in Specification (1). In Specification (2) in Panel Class A for HKI sectors, all tests show that no problems of spatial autocorrelation are associated with the results. In Specification (3) in Panel Class A for HKI sectors, only one test (Moran's I test in spatial error model) shows the results suffer from the problem from spatial autocorrelation.

8. Conclusions

This paper adopted an evolutionary framework to industrial resilience, which emphasizes the ability of an economy to recover from a shock in terms of its capacity to develop new growth paths after a shock. We tested this framework in the context of regions in the European Union. To this end, we explored a new dependent variable of regional resilience. Instead of looking at the vulnerability of regions to a shock (conventionally measured as a decline in output levels) and the ability to recover from a shock (conventionally measured as a return to previous output levels, or to new equilibrium output levels), we looked at the extent to which the ability of regions to develop new industries has been affected by a shock (measured either as maintaining high industry entry levels or even improving entry levels after a shock).

Our analyses show that European regions differ widely in their ability to create new industry paths after the 2008 crisis. Industrial relatedness (measured as the average relatedness between existing specialized industries in the region to the set of industries not yet present in the region) exhibits a positive effect on regional resilience when resilient regions are defined as those that show persistence of high entry levels in all sectors and knowledge-intensive sectors after the crisis. Put differently, industrial relatedness is an important predictor in terms of keeping high entry levels of new industries in knowledge-intensive sectors. For low knowledge-intensive sectors, industrial relatedness does not show any explanatory power on regional resilience. Unexpectedly, we do not find a significant effect of related and unrelated variety on regional resilience. Population density and level of GDP had a positive/negative effect on keeping high entry levels for all sectors, but for high knowledge-intensive sectors, the effect of GDP level was non-significant. For low knowledge-intensive sectors, only average GDP growth rate had a positive effect on being resilient.

A potential drawback of our study is the relatively short period that we could look at after the crisis (2008-2012), as one expects the development of new industries to be a long-term process. Moreover, our dependent variable does not account for the impact of industry entry levels on total output levels in the region. It would therefore be interesting to take up in future research to what extent high industry entry levels in regions also generate higher regional production or employment levels. This is likely to depend on the relative importance of the new industries in the region, and the extent to which a region has shifted away from obsolescent industries and moved into new sectors that are fast-growing, more advanced (Groot et al. 2011) and have a higher degree of complexity (Hausmann and Hidalgo 2010). And are resilient regions in our definition also resilient regions in the more conventional meaning? That is, do regions with a low vulnerability to shocks and/or a strong recovery capacity also show a strong post-crisis ability to develop new industries? Or instead, do deep recessions in regions trigger a stronger capacity of regions to restructure their economies in a fundamental way and release the development of new growth paths?

This paper has explored whether relatedness and variety, in terms of industrial relatedness and related and unrelated variety, matter for regional resilience, as these concepts are tightly linked to our evolutionary take on resilience. However, future research on regional resilience should also include other explanatory factors, like networks and institutions (Boschma 2015). In the network literature, there is relevant work on what types of networks are more resilient (e.g. Fleming et al 2007), but so far, this has hardly been applied to the study of resilience of regions (Vicente et al. 2011; Balland et al. 2013; Crespo et al. 2014). The same applies to the impact of institutions on the sensitivity of regions to shocks and their capacity to develop new growth paths after, which has not yet been fully explored in the regional resilience literature (Bristow 2010; Hassink 2010; Wink 2012; Dawley 2013). These issues are crucial for increasing our understanding of the geography of resilience, which is still limited due to the current embryonic state of the empirical literature on regional resilience.

Table 4 Probability of being resilient regions: all sectors

Variable	Class A + Class B			Class A			Class B		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ind_related	0.0850	0.335	0.436*	0.107	2.303***	1.678***	0.0718	-0.226	0.0718
	(0.191)	(0.409)	(0.229)	(0.232)	(0.746)	(0.558)	(0.238)	(0.511)	(0.238)
RV		1.291			-0.852			1.983	
		(1.177)			(2.179)			(1.450)	
UV		0.620			-1.727			1.319	
		(0.756)			(1.675)			(0.897)	
g4_gdppc		-0.0595			-0.309			0.100	
		(0.241)			(0.629)			(0.237)	
Los		0.778			-1.695			1.506	
		(0.956)			(1.657)			(1.215)	
pop_den (log)		0.773**	0.509**		1.475**	0.915**		0.609	
		(0.323)	(0.224)		(0.604)	(0.425)		(0.379)	
GDP (log)		-1.333**	-0.967***		-4.493***	-3.577***		-0.572	
		(0.606)	(0.293)		(1.520)	(1.159)		(0.629)	
Share_S&T (log)		0.0583			1.386***	0.598		-0.330	
		(0.381)			(0.498)	(0.456)		(0.449)	
Gross capital_emp (log)		0.296			-0.681			0.356	
		(0.427)			(1.075)			(0.467)	
EQI		-0.135			2.244**	1.520**		-0.417	
		(0.358)			(0.978)	(0.745)		(0.366)	
Constant	-1.781***	-2.079***	-1.947***	-2.922***	-5.266***	-4.181***	-2.166***	-2.545***	-2.166***
	(0.217)	(0.295)	(0.256)	(0.365)	(1.243)	(0.820)	(0.257)	(0.386)	(0.257)
Observations	173	163	164	156	148	148	165	155	165
Pseudo R-squared	0.0010	0.0993	0.0739	0.0013	0.3744	0.2628	0.0007	0.0989	0.0007

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Panel "Class A", regions in Class B are excluded. In Panel "Class B", regions in Class A are excluded.

Table 5 Probability of being resilient regions: HKI sectors

Variable	Class A +Class B			Class A			Class B		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ind_related	0.345	0.911	0.464	0.596*	1.918*	0.998**	0.101	-0.0953	-0.00661
	(0.288)	(0.605)	(0.330)	(0.360)	(1.047)	(0.478)	(0.396)	(0.552)	(0.386)
RV		-0.484			-1.403			0.915	
		(1.165)			(1.850)			(2.330)	
UV		-1.515			-3.683*	-1.328***		0.216	
		(0.971)			(1.889)	(0.510)		(1.439)	
g4_gdppc		-0.630*	-0.0743		-2.169*	-1.066		-0.438	
		(0.370)	(0.230)		(1.187)	(0.914)		(0.398)	
Los		-0.905			-2.336			0.388	
		(1.007)			(1.712)			(1.677)	
pop_den (log)		1.274**	0.526**		2.130***	1.610***		1.056*	0.256
		(0.511)	(0.211)		(0.813)	(0.433)		(0.600)	(0.460)
GDP (log)		-0.224			-0.421			0.119	
		(0.727)			(1.144)			(0.910)	
Share_S&T (log)		0.841*	0.242		2.044			0.0163	
		(0.509)	(0.437)		(1.467)			(0.480)	
Gross capital_emp (log)		-1.237			-3.049**	-1.119		-0.961*	-0.323
		(0.757)			(1.445)	(0.784)		(0.552)	(0.463)
EQI		0.198			1.784*	1.227		-0.192	
		(0.758)			(1.035)	(0.749)		(0.771)	
Constant	-2.558***	-3.794***	-2.860***	-3.272***	-7.602***	-5.065***	-3.286***	-4.044***	-3.286***
	(0.299)	(0.754)	(0.357)	(0.418)	(1.426)	(0.664)	(0.418)	(0.785)	(0.457)
Observations	173	163	163	167	158	158	166	156	157
Pseudo R-squared	0.0133	0.2159	0.0884	0.0310	0.4228	0.3065	0.0011	0.1255	0.0162

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Panel "Class A", regions in Class B are excluded. In Panel "Class B", regions in Class A are excluded.

Table 6 Probability of being resilient regions: LKI sectors

Variable	Class A +Class B			Class A			Class B		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ind_related	-0.203	0.235	-0.279	-0.172	0.118	-0.222	-0.206	0.298	-0.283
	(0.253)	(0.453)	(0.258)	(0.509)	(0.852)	(0.465)	(0.273)	(0.480)	(0.274)
RV		-0.761			0.660			-0.941	
		(1.036)			(1.031)			(1.126)	
UV		-0.909			-0.951			-0.972	
		(0.692)			(0.787)			(0.744)	
g4_gdppc		0.452*	0.585***		1.034***	0.919***		0.420*	0.522**
		(0.240)	(0.204)		(0.267)	(0.180)		(0.247)	(0.213)
Los		-0.938			0.163			-1.090	
		(0.743)			(0.770)			(0.809)	
pop_den (log)		0.671**	0.00472		-1.610			0.709**	0.0896
		(0.278)	(0.241)		(2.233)			(0.289)	(0.243)
GDP (log)		-0.806			-0.189			-0.827	
		(0.519)			(1.152)			(0.532)	
Share_S&T (log)		-0.287			0.00546			-0.285	
		(0.384)			(0.500)			(0.401)	
Gross capital_emp (log)		0.188			-0.671			0.265	
		(0.477)			(1.374)			(0.499)	
EQI		0.0514			0.831			0.0166	
		(0.334)			(0.771)			(0.347)	
Constant	-2.233***	-2.553***	-2.323***	-4.368***	-6.413***	-4.730***	-2.359***	-2.655***	-2.423***
	(0.260)	(0.321)	(0.280)	(0.718)	(1.777)	(0.704)	(0.276)	(0.339)	(0.299)
Observations	173	163	164	158	148	151	171	161	162
Pseudo R-squared	0.0060	0.1235	0.0686	0.0028	0.2625	0.1154	0.0061	0.1140	0.0582

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Panel "Class A", regions in Class B are excluded. In Panel "Class B", regions in Class A are excluded.

Acknowledgements

The original dataset was geocoded and cleaned by Nicola Cortinovis from Utrecht University. See Cortinovis and Van Oort (2015) for more details in terms of construction of the dataset. We are grateful for the financial support from the Resilient Cities project supported by the JPI (Joint Programming Initiative) Urban Europe program.

References:

Balland, P.A., Rigby, D. and R. Boschma (2015), 'The technological resilience of cities', *Cambridge Journal of Regions, Economy and Society*, **8**, 167-184.

Balland, P.A., Suire, R. and Vicente, J. (2013), 'Structural and geographical patterns of knowledge networks in emerging technological standards: Evidence from the European GNSS Industry', *Economics of Innovation and New Technology*, **22 (1)**, 47-72

Boschma, R. (2015), 'Towards an evolutionary perspective on regional resilience', *Regional Studies*, **49 (5)**, 733-751.

Boschma, R. and Lambooy, J. (1999), 'The prospects of an adjustment policy based on collective learning in old industrial regions', *Geojournal*, **49(4)**, 391–399.

Boschma, R. and Martin, R. (2010), 'The aims and scope of evolutionary economic geography', in: R. Boschma and R. Martin (eds.), *The Handbook of Evolutionary Economic Geography*. Edward Elgar: Cheltenham, pp. 3-39.

Boschma, R., Minondo, A. and Navarro, M. (2013), 'The Emergence of New Industries at the Regional Level in Spain: A Proximity Approach Based on Product Relatedness', *Economic Geography*, **89(1)**, 29-51.

Bristow, G. (2010), 'Resilient regions: re-'place'ing regional competitiveness', *Cambridge Journal of Regions, Economy and Society*, **3**, 153–167

Bristow, G. and A. Healy (2014), 'Regional resilience: an agency perspective', *Regional Studies.* **48 (5)**, 923-935.

Cappello, R., A. Caragliu and U. Fratesi (2015), 'Spatial heterogeneity in the costs of the economic crisis in Europe: are cities sources of regional resilience?' *Journal of Economic Geography*, **15**, 951-972.

Castaldi, C., Frenken, K. and Los, B. (2015), 'Related Variety, Unrelated Variety and Technological Breakthroughs: An analysis of US State-Level Patenting', *Regional Studies*, **49(5)**, 767-781.

Charron, N., Dijkstra, L. and Lapuente, V. (2014), 'Regional Governance Matters: Quality of Government within European Union Member States', *Regional Studies*, **48(1)**, 68-90. DOI:10.1080/00343404.2013.770141

Charron, N., Lapuente, V. and Rothstein, B. (2013), *Quality of Government and Corruption from a European Perspective: A Comparative Study of Good Governance in EU Regions*. Edward Elgar Publishing: Cheltenham.

Cortinovis, N. and van Oort, F. (2015), ‘Variety, economic growth and knowledge intensity of European regions: a spatial panel analysis’, *The Annals of Regional Science*, 55(1), 7-32.

Cortinovis, N., Xiao, J., Boschma, R. and Van Oort, F. (2016), ‘Quality of government and social capital as drivers of regional diversification in Europe’, Urban and regional research center, Utrecht University: Utrecht, the Netherlands.

Christopherson, S. J. Michie and P. Tyler (2010), ‘Regional resilience: theoretical and empirical perspectives’, *Cambridge Journal of Regions, Economy and Society*, **3**, 3–10.

Crespo, J., R. Suire and J. Vicente (2014), ‘Lock-in or lock-out? How structural properties of knowledge networks affect regional resilience’, *Journal of Economic Geography*, 14, 199-219.

Davies, S. (2011), ‘Regional resilience in the 2008–2010 downturn: comparative evidence from European countries’, *Cambridge Journal of Regions, Economy and Society*, **4**, 369–382.

Dawley, S. (2013), ‘Creating new paths? Offshore wind, policy activism, and peripheral region development’, *Economic Geography*, **90 (1)**, 91-112.

Diodato, D. and A.Weterings (2015), ‘The resilience of regional labour markets to economic shocks: Exploring the role of interactions among firms and workers’, *Journal of Economic Geography*, **15 (4)**, 723-742.

Eriksson, R., M. Henning and A. Otto (2015), ‘Industrial and geographical mobility of workers exiting the Swedish and West German shipbuilding industry 1970-2000’, working paper.

Essletzbichler, J. (2007), ‘Diversity, Stability and Regional Growth in the United States, 1975-2002’, in: K. Frenken (ed.), *Applied Evolutionary Economics and Economic Geography*. Edward Edgar: Cheltenham, pp. 203-299.

Eurostat (2015), High-tech industry and knowledge-intensive services (htec), Annex 3, Eurostat:Luxembourg, http://ec.europa.eu/eurostat/cache/metadata/DE/htec_esms.htm#contact1455195414029.

Fingleton, B., H. Garretsen, R. Martin (2012), ‘Recessionary shocks and regional employment: Evidence on the resilience of U.K. regions’, *Journal of Regional Science*, **52 (1)**, 109-133.

Fleming, L., Mingo, S., Chen, D. (2007), ‘Collaborative brokerage, generative creativity and creative success’, *Administrative Science Quarterly*, **52 (3)**, 443-475.

Frenken, K., Van Oort, F. and Verburg, T. (2007), ‘Related Variety, Unrelated Variety and Regional Economic Growth’, *Regional Studies*, **41(5)**, 685-697.

Grabher, G. (1993), ‘The weakness of strong ties: the lock-in of regional development in the Ruhr area’, in G. Grabher (ed.), *The Embedded Firm*. Routledge: London, pp. 255–277.

Groot, S.P.T., J.L.Möhlmann, J.H. Garretsen, H.L.F. de Groot (2011), ‘The crisis sensitivity of European countries and regions: stylized facts and spatial heterogeneity’, *Cambridge Journal of Regions, Economy and Society,* **4 (3)**, 437-456.

Hartog, M., R. Boschma and M. Sotarauta (2012), ‘The impact of related variety on regional employment growth in Finland 1993-2006. High-tech versus medium/low-tech’, *Industry and Innovation*, **19 (6)**, 459-476.

Hassink, R. (2005), ‘How to unlock regional economies from path dependency? From learning region to learning cluster’, *European Planning Studies,* **13**, 521–535

Hassink, R. (2010), ‘Regional resilience: a promising concept to explain differences in regional economic adaptability?’ *Cambridge Journal of Regions, Economy and Society,* **3**, 45–58.

Hatzichronoglou, T. (1997), ‘Revision of the High-Technology Sector and Product Classification’, OECD Science, Technology and Industry Working Papers, 1997/02, OECD Publishing: Paris, France, http://dx.doi.org/10.1787/134337307632.

Hausmann, R. and Hidalgo, C. A. (2010), ‘Country diversification, product ubiquity, and economic divergence’, Working Paper No. 201, Center for International Department, Havard University: Cambridge, Mass.

Hidalgo, C. A., Klinger, B., Barabási, A.-L. and Hausmann, R. (2007), ‘The Product Space Conditions the Development of Nations’, *Science,* **317 (5837)**, 482-487.

Holm, J.R., C.R. Ostergaard and T.R. Olesen (2014), 'Destruction and Reallocation of Skills Following Large Company Exit', Paper to be presented at DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

Kocornik-Mina, A., T.K.J. McDermott, G. Michaels, F. Rauch (2016), 'Flooded cities', working paper.

Los, B. (2000), 'The empirical performance of a new inter-industry technology spillover measure', in P. P. Saviotti and B. Nooteboom (eds.), *Technology and Knowledge,* Edward Elgar: Cheltenham, pp. 118-151.

Martin, P., T. Mayer and F. Mayneris (2014), 'Are clusters more resilient in crises? Evidence from French exporters in 2008-2009', working paper.

Martin, R. (2012), 'Regional economic resilience, hysteresis and recessionary shocks', *Journal of Economic Geography*, **12**, 1–32.

Martin, R and Sunley, P. (2015), 'On the notion of regional economic resilience: conceptualization and explanation', *Journal of Economic Geography,* **15 (1)**, 1-42.

Martin, R. and Sunley, P. (2006), 'Path dependence and regional economic evolution', *Journal of Economic Geography,* **6(4)**, 395-437.

Neffke F., Henning M. (2013), ‘Skill-relatedness and firm diversification’, *Strategic Management Journal*, **34(3)**, 297-316

Neffke, F., Henning, M. and Boschma, R. (2011), ‘How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions’, *Economic Geography*, **87 (3)**, 237-265.

Nyström, K. (2015), ‘Regional resilience to displacements: Explaining the regional capacity to re-employ displaced workers’, working paper.

O’Donoghue, D. and Gleave, B. (2004), ‘A Note on Methods for Measuring Industrial Agglomeration’, *Regional Studies,* **38 (4)**, 419-427.

Pendall, R., Foster, K. A. and Cowell, M., et al. (2008), ‘Resilience and Regions: Building Understanding of the Metaphor’, Mimeo Institute of Urban and Regional Development, Cornell University: Ithaca, NY.

Pendall, R., K. A. Foster and M. Cowell (2010), ‘Resilience and regions: building understanding of the metaphor’, *Cambridge Journal of Regions, Economy and Society*, **3**, 71–84.

Pike, A., Dawley, S. and Tomaney, J. (2010), ‘Resilience, adaptation and adaptability’, *Cambridge Journal of Regions, Economy and Society,* **3**, 59–70

Reggiani, A., T. De Graaf and P. Nijkamp (2002), 'Resilience: An evolutionary approach to spatial economic systems', *Networks and Spatial Economics*, **2**, 211-229.

Rose, A. (2004), 'Defining and measuring economic resilience to disasters', *Disaster Prevention and Management: An International Journal*, **13(4)**, 307–314.

Saviotti, P. and A. Pyka (2004), 'Economic development by the creation of new sectors', *Journal of Evolutionary Economics*, **14(1)**, 1-35.

Simmie, J. and R. Martin (2010), 'The economic resilience of regions: towards an evolutionary approach', *Cambridge Journal of Regions, Economy and Society*, **3**, 27–43.

Swanstrom, T. (2008), 'Regional Resilience: A Critical Examination of the Ecological Framework', Working Paper 2008-07, Institute of Urban and Regional Development, UC Berkeley.

Tian, Z. (2013), 'Measuring Agglomeration Using the Standardized Location Quotient with a Bootstrap Method', *The Journal of Regional Analysis & Policy*, **43(2)**, 186-197.

Vicente, J., Balland, P.A., Brossard, O. (2011), 'Getting into Networks and Clusters: Evidence from the Midi-Pyrenean Global Navigation Satellite Systems (GNSS) Collaboration Network', *Regional Studies*, **45**, 1059-1078.

Wink, R. (2012), 'Institutions and regional economic resilience', HTWK Leipzig.

Zolli, A. and A.M. Healy (2012), *Resilience. Why things bounce back*, Headline Publishing Group: London.

Appendix

Table A1 Description and summary statistics of main variables

Variables	Description	Obs	Mean	Median	Std. Dev.	Min.	Max.
Entry_04-08	Entry number of all sectors for 2004-2008	173	1.46	1.00	1.44	0	9
Entry_HM-KIS_04-08	Entry number of HM-KIS sectors for 2004-2008	173	0.55	0.00	0.77	0	3
Entry_LHM-LKIS_04-08	Entry number of LHM-LKIS sectors for 2004-2008	173	0.68	0.00	0.98	0	6
Entry_08-12	Entry number of all sectors for 2008-2012	173	1.54	1.00	1.43	0	7
Entry_HM-KIS_08-12	Entry number of HM-KIS sectors for 2008-2012	173	0.45	0.00	0.70	0	3
Entry_LHM-LKIS_08-12	Entry number of LHM-LKIS sectors for 2008-2012	173	0.74	0.00	1.00	0	5
ind_related	Technological flexbility	173	0.58	0.62	0.20	0.09	0.93
RV	Related variety	173	3.99	4.16	0.91	1.64	5.78
UV	Unrelated variety	173	1.61	1.53	0.48	0.47	2.92
g4_gdppc	Average growth rates of GDP per capita for 2004-2008	166	0.02	0.02	0.02	-0.02	0.12
Los	Los-index	173	0.16	0.12	0.11	0.07	0.75
pop_den (log)	Population density	164	5.02	4.82	1.00	3.15	8.74
GDP (log)	Level of GDP	173	3.29	3.42	1.07	0.75	6.16
Share_S&T (log)	Shares of workers in science and technology (S&T) in active population (thousand)	163	-1.43	-1.35	0.29	-2.32	-0.87
Gross capital_emp (log)	Gross capital formation per thousand employees	164	2.14	2.37	0.73	-0.50	3.30
EQI	European Quality of Government Index	173	0.14	0.38	0.98	-2.72	1.90

Table A2 Correlation coefficients among main variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Entry_04-08 (1)	1															
Entry_HM-KIS_04-08 (2)	0.65	1														
Entry_LHM-LKIS_04-08 (3)	0.76	0.15	1													
Entry_08-12 (4)	0.15	0.15	-0.01	1												
Entry_HM-KIS_08-12 (5)	0.25	0.24	0.11	0.55	1											
Entry_LHM-LKIS_08-12 (6)	0.01	0.09	-0.09	0.74	0.11	1										
ind_related (7)	0.09	0.15	-0.03	-0.04	0.09	-0.10	1									
RV (8)	0.18	0.16	0.12	0.06	0.07	0.15	0.32	1								
UV (9)	-0.12	-0.18	-0.09	0.03	-0.05	-0.11	0.17	-0.37	1							
g4_gdppc (10)	0.08	0.03	0.05	0.16	0.05	0.24	0.04	0.07	0.13	1						
Los (11)	-0.09	-0.05	-0.06	-0.09	-0.02	-0.10	-0.22	-0.74	-0.24	-0.15	1					
pop_den (log) (12)	0.20	0.29	0.11	0.05	0.18	0.04	0.16	-0.18	0.19	0.07	0.05	1				
GDP (log) (13)	0.05	0.16	0.00	-0.16	0.08	-0.15	0.52	0.10	0.13	-0.33	-0.08	0.56	1			
Share_S&T (log) (14)	0.09	0.23	0.09	-0.06	0.17	-0.08	0.06	-0.19	0.12	-0.10	0.13	0.64	0.58	1		
Gross capital_emp (log) (15)	-0.12	-0.03	-0.03	-0.18	-0.01	-0.17	-0.13	-0.31	0.09	-0.64	0.23	0.22	0.52	0.47	1	
EQI (16)	-0.05	0.05	-0.01	-0.18	0.08	-0.17	-0.13	-0.14	-0.05	-0.26	0.15	0.27	0.43	0.56	0.56	1

Table A3 Robustness check - Probability of being resilient regions: probit/OLS model

Variable	Probit						OLS					
	All			HKI			All			HKI		
	Class A			Class A			Class A			Class A		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ind_related	0.0545	1.155***	0.820***	0.281*	1.125**	0.558**	0.00504	0.0643**	0.0491*	0.0195*	0.0364	0.0249*
	(0.117)	(0.340)	(0.285)	(0.168)	(0.538)	(0.281)	(0.0107)	(0.0303)	(0.0271)	(0.0116)	(0.0260)	(0.0131)
RV		-0.566			-0.720			-0.00664			-0.0682	
		(0.790)			(0.859)			(0.0642)			(0.0624)	
UV		-0.938			-1.983**	-0.701***		-0.0255			-0.0816*	-0.0303*
		(0.627)			(0.876)	(0.259)		(0.0449)			(0.0438)	(0.0165)
g4_gdppc		-0.226			-1.255*	-0.630		-0.0238			-0.0108	
		(0.295)			(0.675)	(0.505)		(0.0238)			(0.0120)	
Los		-0.978			-1.260			-0.0323			-0.0633	
		(0.627)			(0.792)			(0.0481)			(0.0473)	
pop_den (log)		0.733***	0.500**		1.175***	0.691***		0.0403*	0.0445**		0.0281	
		(0.270)	(0.224)		(0.450)	(0.253)		(0.0216)	(0.0200)		(0.0206)	
GDP (log)		-2.203***	-1.729***		-0.311			-0.126**	-0.0914**		0.00178	
		(0.654)	(0.568)		(0.591)			(0.0565)	(0.0403)		(0.0367)	
Share_S&T (log)		0.776***	0.356		1.273*	0.596		0.0352			0.0195	
		(0.295)	(0.247)		(0.747)	(0.523)		(0.0249)			(0.0132)	
Gross capital_emp (log)		-0.387			-1.734**	-0.818		-0.0182			-0.00574	
		(0.431)			(0.861)	(0.544)		(0.0397)			(0.0260)	
EQI		1.053**	0.684*		0.939*	0.396		0.0295			0.00988	
		(0.451)	(0.375)		(0.552)	(0.345)		(0.0187)			(0.0168)	
Constant	-1.635***	-2.721***	-2.192***	-1.790***	-4.282***	-2.875***	0.0513***	0.0533***	0.0543***	0.0420***	0.0449***	0.0417***
	(0.168)	(0.489)	(0.338)	(0.184)	(0.840)	(0.411)	(0.0178)	(0.0179)	(0.0182)	(0.0155)	(0.0163)	(0.0153)
Observations	156	148	148	167	158	158	156	148	148	167	158	167
Pseudo R-squared	0.0015	0.3638	0.2553	0.0328	0.4347	0.3399	-	-	-	-	-	-
R-squared	-	-	-	-	-	-	0.0005	0.1168	0.0759	0.0095	0.1008	0.0319

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Panel "Class A", regions in Class B are excluded.

Table A4 Robustness check - Spatial autocorrelation tests based on OLS model

Model	Tests	All			HKI		
		Class A			Class A		
		(1)	(2)	(3)	(1)	(2)	(3)
Spatial error							
Statistic	Moran's I	0.014	-0.517	-0.590	1.830	0.003	1.664
P-value		0.989	1.395	1.445	0.067	0.997	0.096
Statistic	Lagrange multiplier	0.140	1.608	1.075	1.498	0.822	1.079
P-value		0.708	0.205	0.300	0.221	0.365	0.299
Statistic	Robust Lagrange multiplier	0.922	0.031	0.234	5.044	0.206	1.704
P-value		0.337	0.860	0.629	0.025	0.650	0.192
Spatial lag							
Statistic	Lagrange multiplier	0.158	1.867	1.732	1.002	0.641	0.770
P-value		0.691	0.172	0.188	0.317	0.423	0.380
Statistic	Robust Lagrange multiplier	0.940	0.291	0.891	4.549	0.025	1.396
P-value		0.332	0.590	0.345	0.033	0.873	0.237

Tests are based on OLS regressions in Table A3.