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Original article

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

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Abstract

This article 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. Related and unrelated variety exhibit a positive effect on regional resilience, especially on the entry of knowledge-intensive industries after the shock.

JEL classification: 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. At the same time, concerns have been raised about the precise meaning of resilience, its definition and conceptualization, the appropriate framework to analyze resilience, and its main determinants (Christopherson *et al.*, 2010; Hassink, 2010; Capello *et al.*, 2015; Martin and Sunley, 2015).

This article aims to contribute to the resilience literature in three main ways. 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. This framework follows Boschma (2015), who argues that resilience should integrate the capacity of an economy to recover from shocks with its capacity to develop new growth paths after a shock. Industrial resilience is thus seen as a key element of long-term economic development.

Second, we apply this framework to study on the resilience of European regions during the global economic crisis that began in 2008. Resilient regions are defined as regions that show high rates of entry of new industry specializations before and after the shock, as well as regions that shift from a state of low rate of entry before the crisis to a state of high rate of entry during and after the crisis. We thus focus on the capacity of regional economies to develop new industrial specializations when confronted with the crisis. Such a capacity is reflected by an ability to either maintain a high rate of entry during the crisis or to develop a high rate of entry in response to the crisis. This definition follows the evolutionary approach and makes our analysis complementary to other studies on resilience of European countries and regions (Davies, 2011; Groot *et al.*, 2011; Capello *et al.*, 2015).

Third, we set up an econometric model to analyze the influence that local economic structure has on the probability that a region in Europe is resilient. To this end, we focus on the influence of related and unrelated variety. This is motivated by a large literature on regional innovation and growth which claims that local presence of related industries facilitates not only interindustry job mobility but also provides better opportunities for recombinations across industries from which new industry specializations may develop (Frenken *et al.*, 2007, Neffke *et al.*, 2011, Boschma *et al.*, 2013). At the same time, although recombinations between unrelated industries may be more difficult and less frequent, there are arguments in favor of that combinations between unrelated activities could stimulate more radically new specializations (cf. Castaldi *et al.*, 2015). Based on this line of argument, we hypothesize that related and unrelated variety have a positive influence on regional resilience and use an econometric model to estimate their role in explaining differences in resilience across regions in Europe.

While resilience is an issue at many levels, such as at the level of nations, regions and cities, our focus is on regions, i.e. the subnational scale. There are two main motivations for this. First, as we show in this article, there are typically significant differences in resilience across regions that operate under the same national institutional framework conditions. This means that local conditions matter. Second, compared to whole nations, regions are often more specialized in certain industries which means that issues associated with developing new industry specializations in the wake of economic crises are often more pressing at the regional level.[1] Taken together, this implies that the regional level represents a pertinent level of analysis of resilience. A better understanding of regional heterogeneity in resilience is not only important for the literature focusing on regions as such but also for the more general literature on economic resilience. Knowledge of the role of regional determinants could, for example, also productively inform the discussion of resilience at the level of countries.

The structure of the article 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 and the methodology, after which we present the main findings and robustness checks. 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 (Groot *et al.*, 2011; Martin *et al.*, 2013) or natural disasters, like the flooding of cities (Kocornik-Mina *et al.*, 2015). 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 (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 neoclassical 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 preexisting equilibrium

1 One example in this regard is the region of Detroit in the United States.

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.* (2010), 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 industrial knowledge base. Building on a large literature on regional innovation and growth, Boschma (2015) proposed two key evolutionary variables, that is, related and unrelated variety (Frenken *et al.*, 2007) that might affect regional resilience. Regions with a diverse set of industries 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, 2017). This is because redundant employees are expected to find jobs more easily in

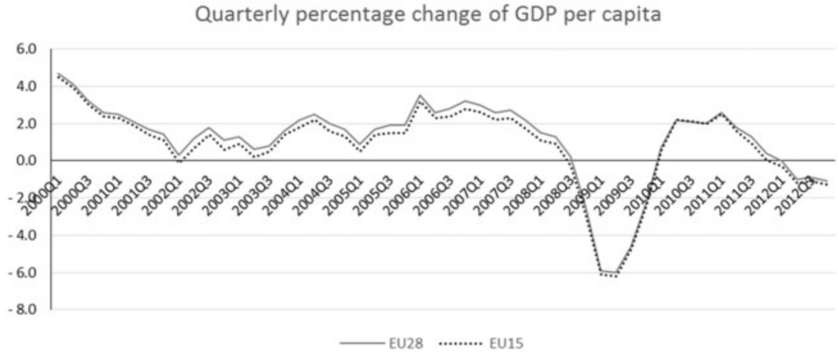

Figure 1. Quarterly percentage change of GDP per capita from 2000 to 2012. *Note:* Measured by percentage change compared to same period in previous year. *Data source:* Eurostat

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, 2017). 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 US 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 and, thus, regional resilience. 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.

Taking such an evolutionary perspective on regional resilience has implications for the choice of the dependent and independent variables in our framework. In sum, we define regions being resilient when a shock has not eroded the ability of regions to diversify and develop new industries, or has even improved their capacity to develop new growth paths. We expect that both related and unrelated variety in a region have a positive effect on regional resilience, mainly because they provide opportunities to make new recombinations across industries from which new industry specializations may develop (Frenken *et al.*, 2007; Neffke *et al.*, 2011; Boschma *et al.*, 2013; Castaldi *et al.*, 2015). We will employ an econometric model to estimate their role in explaining differences in resilience across European regions.

3. Data

From 2008 to 2010, a deep economic crisis swept over Europe. Figure 1 shows quarterly percentage change of gross domestic product (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. This period which includes a significant economic shock provides an interesting period to study resilience.

We use employment data from the Orbis database, compiled by Bureau Van Dijk, covering the period 2004–2012. The data set has been substantially processed[2] by summarizing employment into 173 NUTS2 regions (using the 2010 classification) in 12 European countries and 323 tradable NACE2 (version 2) four-digit sectors.[3] The 12 countries cover all main parts of the European Union (EU): 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).[4]

Among the 323 sectors, there are 222 manufacturing sectors, 35 service sectors and 66 other sectors.[5] Because regions might differ in their ability to create new high knowledge-intensive (HKI) versus low knowledge-intensive (LKI) industries, we distinguish between HKI industries (high-tech and medium-high-tech manufacturing sectors and knowledge-intensive services) and LKI industries (medium-low-tech and low-tech manufacturing sectors and less knowledge-intensive services), see the Organisation for Economic Co-operation and Development industry classification (Hatzichronoglou, 1997; Eurostat, 2015). 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 data set contains 92 HKI-sectors, 165 LKI-sectors, and 66 other sectors.

4. Measuring resilience

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

As discussed before, a main argument in the recent literature in resilience is that one should not take structural change for granted and only observe it indirectly through new equilibrium regional growth paths. Instead, this literature argues that structural change should be part of the definition of regional resilience and accordingly measure it through the ability of regions to develop new industries. A successful response to a shock by a region (high resilience) is thus reflected in an ability to restructure and reorient its regional resources (capital, labor, knowledge, institutions, networks, etc.) and move its regional economy into new industry specializations. Consistent with this, we compare the levels of entry of new specialized industries[6] in regions before and after the crisis. We divide our data into two 4-year periods: a prerecession period (2004–2008) and a period during and after the recession (2008–2012).

We identify an entry of a new industry in a region as a situation in which that region becomes specialized in an industry the region was not specialized in before. This is gauged by a location quotient (LQ) index which measures the level of industrial composition for each region relative to the average level of industrial composition in each country. However, there is no consensus in the literature about the cutoff value of the LQ index in terms of delimiting industrial agglomeration (O'Donoghue and Gleave, 2004). We set three criteria to identify specialized industries.

First, the LQ must be greater than 1 [see equation (1)], which means the concentration in industry i in region r is higher than the average level in the country.

$$LQ_{ic} = \left(\frac{E_{ir}/E_{*r}}{E_{i*,c}/E_{**,\ c}}\right) > 1 \tag{1}$$

Second, the employment in industry i in region r is higher than the average employment of all industries in region r [see equation (2)], which means industry i is one of the major sectors in region r.

$$E_{ir} > \overline{E_{*r}}. \tag{2}$$

Third, the employment in industry i in region r is higher than the average employment in industry i of all regions in that country [see equation (3)], which means region r is one of the major regions for industry i for that country.

2 See Cortinovis and van Oort (2015) for more details in terms of construction of the data set.

3 Compared with the original data set, the data set used in this article 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 data set or because the countries have one NUTS2 region only, and so no variation within these countries can be captured with the data.

4 We divide countries into Western, Eastern, Northern, and Southern European countries in accordance to the typology by the United Nations Statistics Division.

5 Other sectors include industries with the following NACE2 code: 01–03, 05–09, 35–39, and 41–43.

6 We use "entry of new specialized industries" and "entry of new industries" interchangeably in this article.

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

Variables	2004–2008		2008–2012	
	GDP (log)	Employment (log)	GDP (log)	Employment (log)
All sectors	−0.0325	0.3832	0.1330	0.4026
	(0.6712)	(0.0000)	(0.0810)	(0.0000)
HKI	0.0622	0.3527	0.1890	0.3688
	(0.4162)	(0.0000)	(0.0128)	(0.0000)
LKI	−0.0825	0.2537	0.0310	0.2670
	(0.2806)	(0.0010)	(0.6854)	(0.0004)

Note: Significance level in square brackets. Data source: Cambridge Econometrics regional database and Eurostat regional database.

$$E_{ir} > \overline{E_{i*,c}}, \tag{3}$$

where E refers to employment; the subscripts i, r, and c refer to industry i, region r, and country c, respectively; and the subscript * refers to all industries or all regions in each region or country.

In addition, we account for the absolute employment growth in each sector–region combination and include it as an additional criterion to identify entry of a new specialized industry.[7] The reason for this is that we want 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 define an entry of a new industry if the industry is found to be specialized by region r at year t but not at year $t-4$, and if region r 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, respectively.

One source of bias with this methodology is that entry of new specialized industries may be positively related to the market size of regions. To examine whether this is an issue in our empirical context, we calculate the correlations between entry numbers and levels of GDP or employment (in logarithmic forms).[8] As shown in Table 1, we do not find systematically high correlations between entry numbers and levels of GDP or employment.

Figure 2 shows the entry numbers of new specialized industries for all sectors (the left graphs), HKI sectors (the middle graphs), and LKI sectors (the right graphs) of the 173 NUTS2 European regions for the period of 2004–2008 (the upper graphs) and the period of 2008–2012 (the lower graphs), respectively. In Figure 2, we divide regions for the both periods based on three ranges of percentiles of entry numbers during the period of 2004–2008: regions below the 75th percentile of entry number, regions between the 75th percentile and the 90th percentile of entry number, and regions above the 90th percentile of entry number.

During the period of 2004–2008, regions with high entry number of all sectors are frequently located in Northern Italy and three Eastern European countries (Poland, Romania, and Bulgaria). During the period of 2008–2012, the pattern slightly changes as some abovementioned regions lose their status in terms of a high entry number of all sectors. Instead, we see more regions in Germany and the Netherlands exhibiting a high entry number of all sectors. In terms of HKI sectors, we find that regions with a high entry number are frequently located in some regions in Germany, Denmark, Northern Italy, and three Eastern European countries (Poland, Romania, and Bulgaria) during the period of 2004–2008. During the period of 2008–2012, the pattern slightly changes as regions with a high entry number are more concentrated toward regions in Germany. In terms of LKI sectors, we find that regions with a high entry number are sparsely distributed but still be more frequently found in three Eastern European countries (Poland, Romania, and Bulgaria) during the period of 2004–2008. During the period of 2008–2012, we also find that regions with a high entry number are concentrating toward regions in Germany.

A main message from Figure 2 is that compared to the period of 2004–2008, regions with a high entry number (all, HKI, and LKI sectors) tend to concentrate toward regions in Germany and the Netherlands. We report entry numbers for all regions included in the analysis for each period in Table A1 (all sectors), Table A2 (HKI sectors), and Table A3 (LKI sectors), respectively.

7 The average growth rates are calculated for each time interval based on employment data from Orbis.
8 GDP and employment are measured at the beginning year of each time interval.

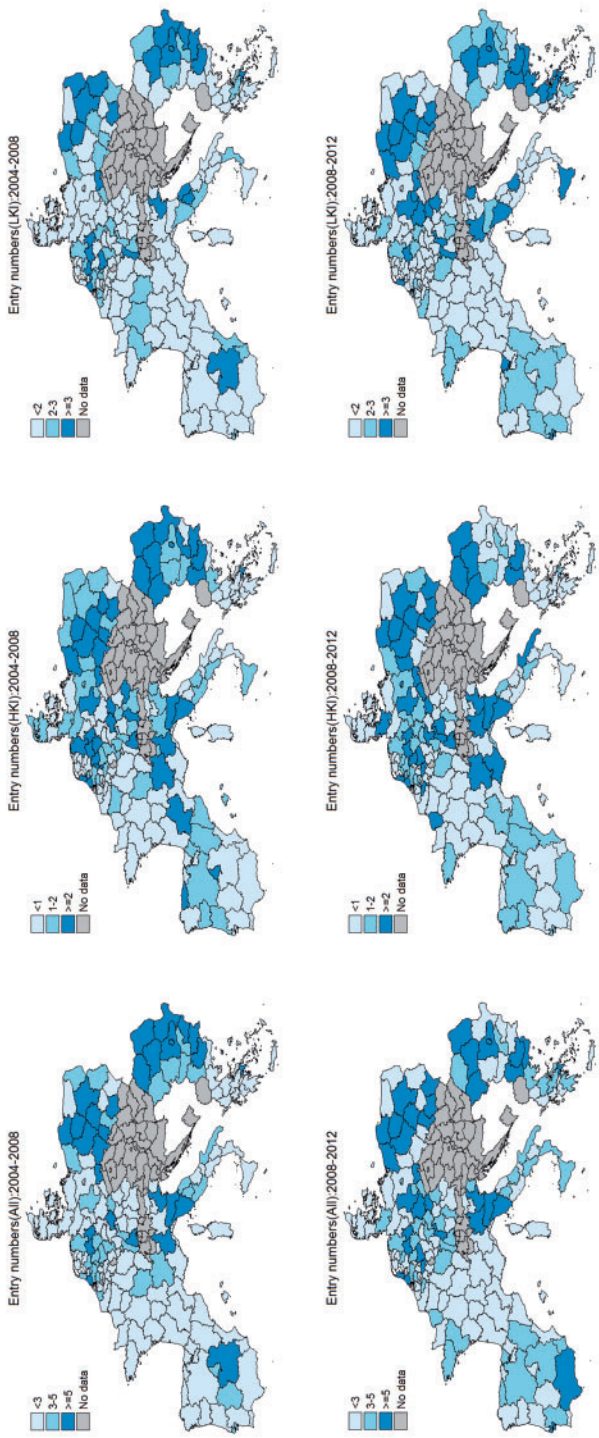

Figure 2. Entry numbers of new specialized industries in European regions.

To compare the dynamics of entry number between the two periods more intuitively, we report the median entry number of new specialized industries (all, HKI, and LKI sectors) by country group, see Table 2. [9] For all sectors, we see that the median entry number of Western and Northern European countries has increased from 1 during the period of 2004–2008 to 2 during the period of 2008–2012. More specifically, this increase is mainly driven by HKI sectors. In contrast, the median entry number of Eastern European countries remains the same between the two periods. It is noticed that we find an increase in median entry number of Southern European countries between the two periods for all sectors. But this pattern is mainly driven by other sectors, as we do not find an increase in median entry number for either HKI or LKI sectors.

4.2 Defining resilience of European regions

To define resilient regions, we employ transition probability analysis to identify regions that show a high rate of entry over the whole period as well as regions that shift from a state of low rate of entry in the precrisis period to a state of high rate of entry during and after the crisis.

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 (4)].

$$p_{mn} = P(g_{2004-2008} = m | g_{2008-2012} = n). \tag{4}$$

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 cells in the diagonal of each panel represent regions with persistently low, medium, and high entry numbers, respectively. In the panel of all sectors, it is noteworthy that all diagonal values are higher than 1. That is, regions show a persistent pattern in terms of entry number of all sectors. In contrast, we find that all probabilities in the off-diagonal are lower than 1, which means the transition between rank groups is more difficult than remaining in the same rank group between the two periods. In the panel of HKI/LKI sectors, we find similar patterns as in the panel of all sectors. The exceptions are that we find higher probabilities (larger than 1) from medium to high group in the panel of HKI sectors, and from medium to low/high to medium in the panel of LKI sectors.

Based on the transition probability analysis, we define resilient regions as those that remain in medium/high rank groups (Type A) and those that transit from low/medium rank groups before the recession (2004–2008) to the high rank group during and after the recession (2008–2012) (Type B).

Figure 3 displays the geographical distribution of resilient regions for all sectors (the left graph), HKI sectors (the middle graph), and LKI sectors (the right graph), respectively. Based on entry dynamics of all sectors, we identify 77 resilient regions, of which there are 52 Type A regions and 25 Type B regions. Based on entry dynamics of HKI sectors, we identify 56 resilient regions, of which there are 36 regions belong to Type A regions and 20 regions belong to Type B regions. Based on dynamics of LKI sectors, we identify 43 resilient regions, of which there are 26 Type A regions and 17 Type B regions. The detailed region list of resilient types can be found in Table A1 (all sectors), Table A2 (HKI sectors), and Table A3 (LKI sectors). We take a closer look at two regions in Germany: Detmond (DEA4) and Köln (DEA2). According to entry dynamic of HKI sectors (see Table A2), Detmond is Type A resilient region, and Köln belongs to Type B resilient region. As a Type A resilient region, Detmond keeps a high level of entry of new specialized HKI sectors during the both two periods. Especially during and after the recession (2008–2012), Detmond acquired six new HKI sectors, such as manufacture of electronic components (NACE code 2611) and manufacture of computers and peripheral equipment (NACE code 2620). Köln, as a Type B resilient region, experienced a transition from a medium to a high level of entry of new specialized industries between the two periods. During 2008–2012, Köln acquired 13 new HKI sectors, such as manufacture of non-domestic cooling and ventilation equipment (NACE code 2825) and manufacture of machinery for metallurgy (NACE code 2891).

9 We use median number instead of average number, as the distribution of the entry number is highly skewed.

Table 2. Median entry numbers of newly specialized industries by country groups

	2004–2008			2008–2012		
	West + North	East	South	West + North	East	South
All sectors	1	5	1	2	5	2
HKI	0	2	0	1	2	0
LKI	1	2	1	1	2	1

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

All		2008–2012		
		Low	Medium	High
2004–2008	Low	1.57	0.78	0.52
	Medium	0.78	1.39	0.84
	High	0.32	0.85	2.06
HKI		2008–2012		
		Low	Medium	High
2004–2008	Low	1.29	0.96	0.40
	Medium	0.88	1.27	1.01
	High	0.55	0.76	2.21
LKI		2008–2012		
		Low	Medium	High
2004–2008	Low	1.14	0.77	0.76
	Medium	1.08	1.04	0.71
	High	0.77	1.24	1.55

5. Econometric analysis

The previous section shows that there is a divergent pattern of industrial resilience across European regions. This section aims to investigate what factors that explain 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.

5.1 Empirical model and variables

To assess which factors that influence the likelihood that a region is resilient, we estimate logit regressions at the regional level. The benchmark model is shown in equation (5):

$$Resi_r = \beta_1 * rv_r + \beta_2 * uv_r + \gamma * Con_r + \delta_c + \epsilon_r, \tag{5}$$

where the subscript r refers to region r; $Resi_r$ is a dummy variable that identifies resilient regions. It equals 1 if the region belongs to the group of resilient regions (as defined in Section 4) and 0 otherwise.

Our variables of main interest is related (rv_r) and unrelated variety (uv_r). As argued before, related industries are likely to have similar skill requirements (Neffke and Henning, 2013; Diodato and Weterings, 2015), and this facilitates interindustry job flows such that workers that leave a declining industry can more easily find a new job on other (related) industries and help to develop those industries into new regional specializations. Furthermore, related industries are also frequently claimed to bode for more productive recombinations across industries from which new industry specializations may develop (Frenken *et al.*, 2007, Neffke *et al.*, 2011, Boschma *et al.*, 2013). We therefore expect that that related variety has a positive influence on the probability that a region is resilient. We further hypothesize that unrelated variety could also have a positive influence on resilience, i.e. both β_1 and β_2 are expected to

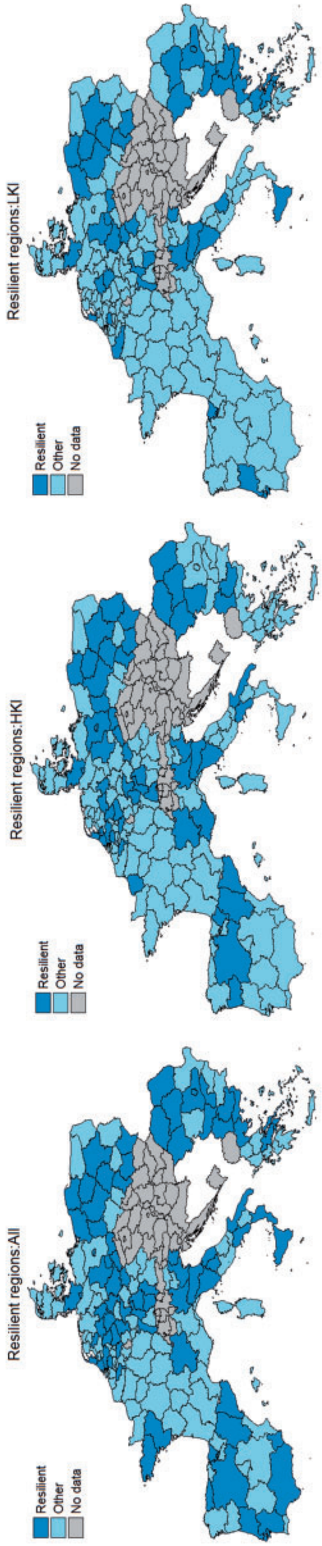

Figure 3. Resilient regions.

be positive. However, unrelated variety might be of less importance compared to related variety. The reason for this is that although recombinations between unrelated industries could induce novelty (cf. Castaldi *et al.*, 2015), it may be more difficult and less frequent. We will test for this by standardizing all estimated coefficients and test whether the magnitude of order of the estimated parameters for related and unrelated variety differs.

To measure 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 two-digit Standard Industrial Classification groups, while related variety was measured as the weighted sum of five-digit variety within each two-digit group. In our analysis, however, sectoral division is based on NACE aggregation scheme (version 2). As pointed out by Cortinovis and van Oort (2015), the use of sections as a boundary to distinguish between relatedness and relatedness can better capture the relatedness among some two-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 four-digit diversity within each section, as in equations (6), (7a), and (7b). We have 323 four-digit NACE sectors that are grouped into 13 sections.

$$UV = \sum\nolimits_{s=1}^{S} P_s \quad log_2\left(\frac{1}{p_s}\right), \tag{6}$$

$$RV = \sum\nolimits_{s=1}^{S} P_s \quad H_s, \tag{7a}$$

$$H_s = \sum_{i \in s} \frac{P_i}{P_s} \; log_2 \left(\frac{1}{{P_i}/{P_s}}\right), \tag{7b}$$

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

In addition to related and unrelated variety, we also control for several confounding factors. In equation (5), Con_r is a vector of control variables at regional level. These are as follows:

- localization economies as captured by the Los index (Los, 2000),
- population density (indicator of urbanization economies),
- average growth rate of GDP per capita,
- the level of GDP,
- 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 refer economies of scale that are external to individual firms but internal to a group of similar industries. Marshall (1920) argued that there are three main sources of localization economies: (i) common labor pool, (ii) knowledge and information spillovers, and (iii) specialized inputs and suppliers. These mechanisms are also likely to facilitate the emergence of new industry specializations. A large scale of similar industries, for example in terms of sharing the same knowledge or technology, is expected to benefit new specializations in industries that are related to the existing "cluster" because the new industry could benefit from sharing workers, gaining spillovers, and use specialized suppliers. We measure localization economies 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 to indicate the technological relatedness for each pair of industries. To derive the proximity index among sectors, 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 × 323 matrix that reflects industrial relatedness in the 173 European regions.

A higher Los index means a 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 (8):

$$Los_c = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(E_{i,r} * E_{j,r} * \phi_{i,j})}{\sum_{i=1}^{n}\sum_{j=1}^{n}(E_{i,r}, *E_{j,r})}, \tag{8}$$

where $\phi_{i,j}$ refers to the proximity index between industry i and j.

The average growth rate of GDP per capita is aimed to reflect growth in local demand within a region as well as to capture the general level of economic opportunities in a region. Our basic hypothesis is that strong local growth facilitates entry of new industries because of favorable overall economic conditions in the region. We measure growth in GDP per capita as the average log difference of GDP per capita in the period 2004–2008. Likewise, the level of GDP captures the absolute size of the regional market as well as the general level of economic development.

Population density and the level of GDP are included as "catch-all" variables. Population density is a typical way to proxy urbanization economies, i.e. external economies of scale associated with the size of a region (or city). A high population density is likely to facilitate entry of new specializations, for example because access to general services and human capital as well as interregional and intraregional infrastructure tends to be more favorable in large and denser regions. At the same time, high population density could also be associated with congestion and high cost levels. Population density thus captures the net effect of, on the one hand, the positive externalities associated with the density of a region, and the negative effects from congestion, on the other hand (Rosenthal and Strange, 2003).

We also control for shares of workers in S&T in active population. The share of workers in S&T aims to reflect availability of local human capital that can sustain and drive the emergence of new industry specialization. It is well documented in the literature that local presence of skilled workers, in particular workers with training in science and engineering, is essential in explaining regional growth and innovation. Human capital is also a common indicator of the "absorptive capacity" of the local economy (Cohen and Levinthal, 1990). In view of this, our basic hypothesis is that the share of S&T workers has a positive influence on entry of new industry specializations. We further control for gross capital formation per thousand employees to capture the net increase in physical assets of local businesses in a region.

The likelihood that a region is resilient is also likely to depend on the quality of the institutions and government that a regional economy operates under (cf. Cortinovis *et al.*, 2017). To control for this, we employ 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 Web site 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. The model also includes country dummy variables, δ_c, which are used to control for fixed country effects.

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 A4[10] and correlation coefficients in Table A5.

5.2 Results

All continuous regressors are standardized before they are included in 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 medium/high rank groups (Type A) and those that transit from the low/medium rank groups to the high rank group (Type B). In the first panel of each table, resilient regions refer to both Type A and Type B regions. In the second panel, resilient regions only refer to Type A regions. In the third panel, resilient regions only refer to Type B regions. In each panel, Specification (1) only includes related variety, unrelated variety, and country dummy variables, while Specification (2) is the full model, where we add all control variables.

In Table 4, where we measure resilient regions based on entry dynamics of all sectors, we find that related variety and unrelated variety both have a positive effect on being resilient regions (both Type A and/or Type B). Based on one-sided z tests after the estimation in Specification (2) of each panel, the coefficient of related variety is significantly

10 There are missing values in some control variables.

Table 4. Probability of being resilient regions: all sectors

Variable	Type A + Type B		Type A		Type B	
	(1)	(2)	(1)	(2)	(1)	(2)
RV	1.519***	3.690***	1.408***	3.387***	1.974***	4.489***
	(0.356)	(1.034)	(0.417)	(1.135)	(0.639)	(1.438)
UV	0.593*	1.646***	0.447	1.363**	1.016**	2.191***
	(0.305)	(0.625)	(0.334)	(0.690)	(0.517)	(0.819)
g4_gdppc		−0.581		−0.948**		−0.0606
		(0.418)		(0.463)		(0.604)
Los		2.101***		1.857**		2.730**
		(0.765)		(0.874)		(1.070)
pop_den (log)		0.632		0.893*		−0.154
		(0.388)		(0.476)		(0.648)
GDP (log)		0.749*		0.698		1.241*
		(0.430)		(0.514)		(0.652)
Share_S&T (log)		−0.111		0.0493		0.0872
		(0.531)		(0.624)		(0.826)
Gross capital_emp (log)		0.0221		0.0656		−0.469
		(0.625)		(0.640)		(1.040)
EQI		−0.289		0.0540		−0.586
		(0.475)		(0.519)		(0.689)
Constant	−0.863	−1.372	−2.032*	−3.656**	−1.233	−0.260
	(0.762)	(1.091)	(1.193)	(1.522)	(0.919)	(1.329)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168	163	143	139	108	106
Pseudo R-squared	0.2035	0.3185	0.1997	0.3368	0.2243	0.3359
One-sided z tests on coefficients after estimation: H0: std_uv1 $\geq$ std_rv1	–	0.0001	–	0.0004	–	0.0014

Note: Robust standard errors in parentheses. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. In Panel "Type A," Type B resilient regions are excluded. In Panel "Type B," Type A resilient regions are excluded.

higher than that of unrelated variety. This is consistent with our baseline hypothesis. It is further evident that the positive effects of both related variety and unrelated variety are stronger on the probability of being a Type B resilient region compared to their effect on the probability of being a Type A resilient region. Related and unrelated variety thus appear to be more important for regions that make a shift from a precrisis state of low rate of entry toward a state of high rate of entry during and after the crisis. This reinforces the idea of related and unrelated variety as critical characteristics of local economies that manage to combat a crisis by introducing new industry specializations.

In terms of control variables, first, the average growth rate of GDP per capita has a negative effect on being Type A resilient regions. This is at odds with expectations. Second, as expected, the Los index is found to have a positive effect on being resilient regions (both Type A and/or Type B), and the positive effect is stronger on the probability of being Type B compared to Type A resilient regions. It is also evident that population density has a weak positive association with the probability of being Type A resilient regions, and that the level of GDP exhibits a positive but yet weakly significant effect on being Type B resilient regions.

Table 5 reports the results where we measure resilient regions based on entry dynamics of HKI sectors. A clear finding is that both related and unrelated variety have a positive effect on being Type B resilient regions. However, neither related nor unrelated variety has a statistically significant effect on being resilient regions (both types) or Type A resilient regions if we include control variables. This confirms the pattern in Table 4. Related and unrelated are primarily of importance for regions that make a shift from low to high rates of entry.

Table 5. Probability of being resilient regions: HKI sectors

Variable	Type A +Type B		Type A		Type B	
	(1)	(2)	(1)	(2)	(1)	(2)
RV	0.872***	1.193	0.845**	1.293	1.186*	4.324**
	(0.319)	(0.918)	(0.402)	(1.085)	(0.612)	(2.052)
UV	0.305	0.271	−0.0305	0.0611	1.079*	2.436*
	(0.289)	(0.638)	(0.342)	(0.756)	(0.606)	(1.303)
g4_gdppc		−0.738		−0.520		−5.452***
		(0.454)		(0.453)		(2.057)
Los		0.452		0.590		2.662*
		(0.794)		(0.897)		(1.573)
pop_den (log)		0.138		−0.203		1.965**
		(0.491)		(0.622)		(0.917)
GDP (log)		1.714***		2.005***		3.078**
		(0.571)		(0.734)		(1.404)
Share_S&T (log)		−0.0396		−0.0891		0.371
		(0.640)		(0.715)		(1.620)
Gross capital_emp (log)		0.0293		0.471		−4.258*
		(0.796)		(1.004)		(2.436)
EQI		−0.669		−0.106		−3.312*
		(0.505)		(0.668)		(1.820)
Constant	−0.365	−0.576	−2.071*	−2.522*	−0.317	−0.925
	(0.695)	(0.997)	(1.198)	(1.410)	(0.735)	(1.624)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	155	150	135	131	88	84
Pseudo R-squared	0.1287	0.2991	0.1545	0.3027	0.1542	0.556
One-sided z tests on coefficients after estimation: H0: std_uv1 ≥ std_rv1	–	–	–	–	–	0.0601

Note: Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$. In Panel "Type A," Type B resilient regions are excluded. In Panel "Type B," Type A resilient regions are excluded.

In terms of control variables, we find that the level of GDP is positive and significant, whereas population density only matters for the probability of being a Type B resilient region. Also, the average growth rate of GDP per capita shows a negative effect on being Type B resilient regions.

In Table 6, where we measure resilient regions based on entry dynamics of LKI sectors, we find an opposite pattern for the effects of related variety and unrelated variety compared to in Table 5. In Table 6, both related and unrelated variety have a positive effect on being resilient regions (both types) and Type A resilient regions. However, neither related nor unrelated variety has a statistically significant effect on being Type B resilient regions if we include control variables. The Los index exhibits a positive effect on being both types of resilient regions and Type A resilient regions.

In summary, we find that related variety and unrelated variety exhibit a positive effect on the probability that a region is resilient. For the baseline estimation, we also find that related variety exhibits a stronger positive effect on being resilient compared to unrelated variety. But when we measure resilient regions by differentiating between HKI and LKI sectors, we find divergent effects of related and unrelated variety. A general pattern is that related variety and unrelated variety are more important for the probability of being a Type B resilient regions (those that transit from the low/medium rank groups to the high rank group) when we measure resilient regions based on entry dynamics of knowledge-intensive and high-tech sectors (HKI sectors). However, related variety and unrelated variety show a positive effect on being Type A resilient regions (those that remain in the medium/high rank groups) when we measure resilient regions based on entry dynamics of LKI sectors. That is, related variety and unrelated variety are important variables to explain the ability of regions that jump from a low level to a high level of entry number for

Table 6. Probability of being resilient regions: LKI sectors

Variable	Type A +Type B		Type A		Type B	
	(1)	(2)	(1)	(2)	(1)	(2)
RV	1.922***	3.906***	1.940**	5.024***	2.210***	2.697
	(0.617)	(1.308)	(0.905)	(1.631)	(0.656)	(1.999)
UV	0.627	1.500**	0.491	1.998**	1.070**	0.986
	(0.431)	(0.699)	(0.607)	(0.978)	(0.496)	(1.239)
g4_gdppc		0.0938		−0.910		1.043*
		(0.413)		(0.606)		(0.591)
Los		2.339**		3.234**		0.928
		(1.055)		(1.324)		(2.014)
pop_den (log)		0.361		0.677		0.0880
		(0.508)		(0.614)		(0.793)
GDP (log)		0.590		0.986		0.790
		(0.535)		(0.671)		(0.733)
Share_S&T (log)		0.131		0.437		0.0738
		(0.561)		(0.898)		(0.585)
Gross capital_emp (log)		−0.101		−0.0314		−0.498
		(0.800)		(0.877)		(1.203)
EQI		0.247		0.290		−0.170
		(0.570)		(0.755)		(0.790)
Constant	−2.570**	−2.866*	−2.681**	−4.017**	−3.109***	−5.051*
	(1.204)	(1.491)	(1.249)	(1.703)	(0.924)	(2.808)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168	163	125	121	104	101
Pseudo R-squared	0.2579	0.3265	0.2271	0.3657	0.2302	0.297
One-sided z tests on coefficients after estimation: H0: std_uv1 $\geq$ std_rv1	–	0.0014	–	0.0006	–	–

Note: Robust standard errors in parentheses. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. In Panel "Type A," Type B resilient regions are excluded. In Panel "Type B," Type A resilient regions are excluded.

HKI sectors, whereas related variety and unrelated variety are important variables to explain the ability of regions that remain in a high level of entry number for LKI sectors.

6. Robustness checks

To check whether our main findings are sensitive to different estimators, we estimate the full model [Specification (2)] for all, HKI, and LKI sectors, respectively, based on probit and ordinary least squares (OLS) models separately (see Tables A6 and A7).[11] The results in terms of the effects of related variety and unrelated variety exhibit a similar pattern with our main findings. It is noteworthy that the coefficients of related variety and unrelated variety are not statistically significant in some OLS regressions (see Table A7; unrelated variety in Column 2; related variety and unrelated variety in Column 4).

7. Conclusions

This article 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 EU. To this end, we explored a new dependent variable of regional resilience. Instead

11 In this section, we focus on checking the sensitivity of the main findings. Therefore, we conduct robustness checks for all three panels of all sectors, for Panel "Type B" of HKI sectors and for Panel "Type A" of LKI sectors.

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. As expected, related variety and unrelated variety turn out to be crucial factors that enhance the probability of a region being resilient. This especially applies to related variety which shows a stronger positive effect on regional resilience. Moreover, related and unrelated variety are more important for the probability of being what we refer to as a Type B resilient region (those that transit from low/medium entry levels to high entry levels after the shock), as compared to Type A resilient regions (those that maintain medium/high entry levels after the shock). When we differentiate between HKI and LKI sectors, we find remarkable differences: related variety and unrelated variety are important factors that explain the ability of regions to jump from low levels to high levels of entry in HKI sectors, while related and unrelated variety have a positive effect on the ability of regions to maintain high entry levels in LKI sectors.

In general, very few of our control variables had a significant impact on regional resilience. Localization economies, as proxied by the Los index, had a positive effect on keeping high entry levels but above all on improving entry levels in all sectors. For entry of HKI sectors, the effect of GDP level was always positive and significant, while population density had a positive effect, and the average growth rate of GDP per capita had a negative effect on the probability of a region to shift from low to high entry levels after the shock. For entry of LKI sectors, only localization economies (as proxied by the Los index) had a positive effect on a region being resilient, as measured by maintaining high entry levels after the shock.

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 definition of resilience captures both related diversification (new industries closely related to existing industries in a region) and unrelated diversification (new industries unrelated to existing industries in a region) in regions. Future research could take up this crucial distinction, and investigate whether resilient regions that are characterized by unrelated diversification show higher long-term growth rates, as compared to resilient regions that diversify into sectors that are more closely related to those specialized in (Boschma, 2017). Finally, 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 and 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 postcrisis 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 article has explored whether relatedness and variety, in terms of 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 (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, 2014; 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.

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Appendix

Table A1. Region list of entry number, rank group, and resilient type: all sectors

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
BE10	1	L	2	M	O
BE21	3	M	3	M	A
BE22	2	M	1	L	O
BE23	2	M	0	L	O
BE24	0	L	1	L	O
BE25	3	M	1	L	O
BE31	0	L	0	L	O
BE32	2	M	4	H	B
BE33	1	L	5	H	B
BE34	0	L	1	L	O
BE35	0	L	0	L	O
BG31	3	M	2	M	A
BG32	4	H	4	H	A
BG33	6	H	2	M	O
BG34	10	H	2	M	O
BG41	3	M	9	H	B
BG42	10	H	10	H	A
DE11	1	L	4	H	B
DE12	3	M	6	H	B
DE13	5	H	3	M	O
DE14	2	M	2	M	A
DE21	1	L	1	L	O
DE22	2	M	0	L	O
DE23	0	L	3	M	O
DE24	4	H	6	H	A
DE25	2	M	1	L	O
DE26	5	H	3	M	O
DE27	2	M	3	M	A
DE30	2	M	3	M	A
DE40	1	L	1	L	O
DE50	2	M	2	M	A
DE60	2	M	3	M	A
DE71	1	L	4	H	B
DE72	0	L	2	M	O
DE73	2	M	3	M	A
DE80	2	M	1	L	O
DE91	0	L	2	M	O
DE92	1	L	2	M	O
DE93	1	L	2	M	O
DE94	4	H	3	M	O
DEA1	4	H	4	H	A
DEA2	4	H	14	H	A
DEA3	5	H	5	H	A
DEA4	7	H	6	H	A
DEA5	3	M	3	M	A
DEB1	3	M	2	M	A
DEB2	0	L	2	M	O

(continued)

Table A1. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
DEB3	1	L	1	L	O
DEC0	1	L	1	L	O
DED2	6	H	6	H	A
DED4	2	M	3	M	A
DED5	1	L	4	H	B
DEE0	3	M	5	H	B
DEF0	2	M	4	H	B
DEG0	1	L	6	H	B
DK01	2	M	0	L	O
DK02	0	L	0	L	O
DK03	0	L	1	L	O
DK04	1	L	1	L	O
DK05	1	L	2	M	O
EL11	1	L	5	H	B
EL12	2	M	4	H	B
EL13	1	L	0	L	O
EL14	0	L	3	M	O
EL21	0	L	0	L	O
EL22	0	L	0	L	O
EL23	0	L	2	M	O
EL24	2	M	3	M	A
EL25	0	L	3	M	O
EL30	6	H	7	H	A
EL41	0	L	1	L	O
EL42	0	L	0	L	O
EL43	0	L	0	L	O
ES11	2	M	1	L	O
ES12	2	M	3	M	A
ES13	0	L	0	L	O
ES21	1	L	4	H	B
ES22	1	L	2	M	O
ES23	0	L	1	L	O
ES24	2	M	3	M	A
ES30	3	M	1	L	O
ES41	2	M	3	M	A
ES42	6	H	3	M	O
ES43	3	M	0	L	O
ES51	2	M	2	M	A
ES52	2	M	1	L	O
ES53	1	L	0	L	O
ES61	2	M	5	H	B
ES62	2	M	4	H	B
FR10	0	L	1	L	O
FR21	0	L	0	L	O
FR22	1	L	0	L	O
FR23	1	L	3	M	O
FR24	2	M	1	L	O
FR25	1	L	0	L	O
FR26	4	H	1	L	O
FR30	1	L	2	M	O

(continued)

Table A1. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
FR41	1	L	3	M	O
FR42	3	M	3	M	A
FR43	1	L	0	L	O
FR51	2	M	3	M	A
FR52	0	L	4	H	B
FR53	0	L	1	L	O
FR61	2	M	1	L	O
FR62	2	M	1	L	O
FR63	0	L	0	L	O
FR71	3	M	2	M	A
FR72	0	L	0	L	O
FR81	1	L	1	L	O
FR82	1	L	2	M	O
FR83	0	L	0	L	O
ITC1	5	H	0	L	O
ITC2	1	L	0	L	O
ITC3	1	L	1	L	O
ITC4	1	L	6	H	B
ITF1	1	L	3	M	O
ITF2	1	L	1	L	O
ITF3	2	M	3	M	A
ITF4	3	M	4	H	B
ITF5	1	L	0	L	O
ITF6	2	M	4	H	B
ITG1	2	M	3	M	A
ITG2	1	L	1	L	O
ITH1	1	L	1	L	O
ITH2	1	L	1	L	O
ITH3	5	H	5	H	A
ITH4	1	L	4	H	B
ITH5	5	H	5	H	A
ITI1	5	H	6	H	A
ITI2	3	M	3	M	A
ITI3	3	M	2	M	A
ITI4	3	M	0	L	O
NL11	1	L	0	L	O
NL12	0	L	0	L	O
NL13	0	L	0	L	O
NL21	2	M	3	M	A
NL22	4	H	1	L	O
NL23	1	L	1	L	O
NL31	1	L	2	M	O
NL32	4	H	10	H	A
NL33	7	H	5	H	A
NL34	1	L	2	M	O
NL41	3	M	3	M	A
NL42	4	H	1	L	O
PL11	6	H	9	H	A
PL12	6	H	7	H	A
PL21	7	H	10	H	A

(continued)

Table A1. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
PL22	3	M	17	H	B
PL31	4	H	2	M	O
PL32	2	M	6	H	B
PL33	2	M	0	L	O
PL34	4	H	1	L	O
PL41	6	H	14	H	A
PL42	4	H	6	H	A
PL43	2	M	2	M	A
PL51	5	H	2	M	O
PL52	5	H	2	M	O
PL61	7	H	8	H	A
PL62	2	M	0	L	O
PL63	5	H	9	H	A
PT11	1	L	1	L	O
PT15	0	L	0	L	O
PT16	2	M	2	M	A
PT17	3	M	6	H	B
PT18	0	L	4	H	B
RO11	5	H	4	H	A
RO12	8	H	7	H	A
RO21	8	H	5	H	A
RO22	8	H	2	M	O
RO31	5	H	7	H	A
RO32	9	H	3	M	O
RO41	4	H	2	M	O
RO42	3	M	7	H	B

Note: Rank groups "L," "M," and "H" refer to "Low," "Medium," and "High," respectively. Resilient Type "A" refers to resilient regions that remain in the high/medium rank groups; resilient Type "B" refers to resilient regions that transit from the low/medium rank groups (2004–2008) to the high rank group (2008–2012); and resilient Type "O" refers to other regions.

Table A2. Region list of entry number, rank group, and resilient type: HKI sectors

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
BE10	1	M	2	H	B
BE21	1	M	1	M	A
BE22	0	L	0	L	O
BE23	0	L	0	L	O
BE24	0	L	1	M	O
BE25	0	L	0	L	O
BE31	0	L	0	L	O
BE32	0	L	4	H	B
BE33	1	M	3	H	B
BE34	0	L	0	L	O
BE35	0	L	0	L	O
BG31	1	M	0	L	O
BG32	2	H	1	M	O
BG33	0	L	0	L	O
BG34	2	H	0	L	O
BG41	2	H	4	H	A
BG42	5	H	5	H	A
DE11	0	L	2	H	B
DE12	1	M	3	H	B
DE13	3	H	2	H	A
DE14	1	M	0	L	O
DE21	1	M	0	L	O
DE22	2	H	0	L	O
DE23	0	L	0	L	O
DE24	3	H	2	H	A
DE25	1	M	0	L	O
DE26	3	H	0	L	O
DE27	2	H	1	M	O
DE30	1	M	2	H	B
DE40	1	M	1	M	A
DE50	0	L	1	M	O
DE60	1	M	1	M	A
DE71	0	L	2	H	B
DE72	0	L	1	M	O
DE73	0	L	1	M	O
DE80	0	L	0	L	O
DE91	0	L	1	M	O
DE92	0	L	1	M	O
DE93	1	M	0	L	O
DE94	2	H	1	M	O
DEA1	3	H	3	H	A
DEA2	1	M	13	H	B
DEA3	2	H	2	H	A
DEA4	4	H	6	H	A
DEA5	2	H	1	M	O
DEB1	1	M	0	L	O
DEB2	0	L	0	L	O
DEB3	1	M	1	M	A
DEC0	1	M	0	L	O
DED2	2	H	2	H	A

(continued)

Table A2. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
DED4	0	L	2	H	B
DED5	1	M	0	L	O
DEE0	2	H	2	H	A
DEF0	1	M	2	H	B
DEG0	0	L	1	M	O
DK01	0	L	0	L	O
DK02	0	L	0	L	O
DK03	0	L	0	L	O
DK04	1	M	0	L	O
DK05	1	M	0	L	O
EL11	0	L	0	L	O
EL12	1	M	0	L	O
EL13	0	L	0	L	O
EL14	0	L	0	L	O
EL21	0	L	0	L	O
EL22	0	L	0	L	O
EL23	0	L	0	L	O
EL24	0	L	0	L	O
EL25	0	L	0	L	O
EL30	2	H	1	M	O
EL41	0	L	0	L	O
EL42	0	L	0	L	O
EL43	0	L	0	L	O
ES11	0	L	1	M	O
ES12	2	H	0	L	O
ES13	0	L	0	L	O
ES21	0	L	0	L	O
ES22	1	M	1	M	A
ES23	0	L	0	L	O
ES24	1	M	1	M	A
ES30	2	H	0	L	O
ES41	1	M	1	M	A
ES42	0	L	0	L	O
ES43	0	L	0	L	O
ES51	1	M	1	M	A
ES52	0	L	1	M	O
ES53	1	M	0	L	O
ES61	0	L	1	M	O
ES62	0	L	0	L	O
FR10	0	L	0	L	O
FR21	0	L	0	L	O
FR22	1	M	0	L	O
FR23	0	L	2	H	B
FR24	0	L	0	L	O
FR25	0	L	0	L	O
FR26	1	M	0	L	O
FR30	0	L	0	L	O
FR41	0	L	1	M	O
FR42	0	L	0	L	O
FR43	0	L	0	L	O

(continued)

Table A2. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
FR51	0	L	0	L	O
FR52	0	L	1	M	O
FR53	0	L	0	L	O
FR61	0	L	0	L	O
FR62	2	H	1	M	O
FR63	0	L	0	L	O
FR71	2	H	2	H	A
FR72	0	L	0	L	O
FR81	0	L	0	L	O
FR82	0	L	2	H	B
FR83	0	L	0	L	O
ITC1	4	H	0	L	O
ITC2	1	M	0	L	O
ITC3	0	L	1	M	O
ITC4	1	M	2	H	B
ITF1	1	M	0	L	O
ITF2	0	L	0	L	O
ITF3	1	M	1	M	A
ITF4	0	L	2	H	B
ITF5	0	L	0	L	O
ITF6	0	L	0	L	O
ITG1	1	M	0	L	O
ITG2	0	L	0	L	O
ITH1	0	L	0	L	O
ITH2	0	L	0	L	O
ITH3	1	M	2	H	B
ITH4	1	M	0	L	O
ITH5	3	H	2	H	A
ITI1	2	H	2	H	A
ITI2	0	L	0	L	O
ITI3	0	L	1	M	O
ITI4	1	M	0	L	O
NL11	0	L	0	L	O
NL12	0	L	0	L	O
NL13	0	L	0	L	O
NL21	0	L	1	M	O
NL22	0	L	1	M	O
NL23	0	L	1	M	O
NL31	1	M	1	M	A
NL32	3	H	2	H	A
NL33	2	H	4	H	A
NL34	0	L	0	L	O
NL41	1	M	1	M	A
NL42	2	H	0	L	O
PL11	4	H	4	H	A
PL12	1	M	3	H	B
PL21	2	H	4	H	A
PL22	1	M	8	H	B
PL31	1	M	1	M	A
PL32	0	L	5	H	B

(continued)

Table A2. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
PL33	2	H	0	L	O
PL34	1	M	0	L	O
PL41	2	H	6	H	A
PL42	2	H	1	M	O
PL43	1	M	2	H	B
PL51	2	H	0	L	O
PL52	2	H	0	L	O
PL61	2	H	3	H	A
PL62	1	M	0	L	O
PL63	1	M	2	H	B
PT11	1	M	1	M	A
PT15	0	L	0	L	O
PT16	1	M	0	L	O
PT17	0	L	1	M	O
PT18	0	L	0	L	O
RO11	2	H	3	H	A
RO12	2	H	2	H	A
RO21	4	H	2	H	A
RO22	2	H	0	L	O
RO31	1	M	0	L	O
RO32	2	H	0	L	O
RO41	1	M	1	M	A
RO42	2	H	4	H	A

Note: Rank groups "L," "M," and "H" refer to "Low," "Medium," and "High," respectively. Resilient Type "A" refers to resilient regions that remain in the high/medium rank groups; resilient Type "B" refers to resilient regions that transit from the low/medium rank groups (2004–2008) to the high rank group (2008–2012); and resilient Type "O" refers to other regions.

Table A3. Region list of entry number, rank group, and resilient type: LKI sectors

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
BE10	0	L	0	L	O
BE21	1	M	2	M	A
BE22	2	H	1	L	O
BE23	2	H	0	L	O
BE24	0	L	0	L	O
BE25	2	H	1	L	O
BE31	0	L	0	L	O
BE32	0	L	0	L	O
BE33	0	L	1	L	O
BE34	0	L	1	L	O
BE35	0	L	0	L	O
BG31	1	M	2	M	A
BG32	2	H	2	M	O
BG33	5	H	2	M	O
BG34	7	H	1	L	O
BG41	0	L	3	H	B
BG42	4	H	5	H	A
DE11	1	M	1	L	O
DE12	2	H	3	H	A
DE13	2	H	1	L	O
DE14	1	M	2	M	A
DE21	0	L	1	L	O
DE22	0	L	0	L	O
DE23	0	L	3	H	B
DE24	1	M	4	H	B
DE25	1	M	1	L	O
DE26	2	H	1	L	O
DE27	0	L	2	M	O
DE30	1	M	1	L	O
DE40	0	L	0	L	O
DE50	1	M	1	L	O
DE60	1	M	1	L	O
DE71	1	M	1	L	O
DE72	0	L	1	L	O
DE73	2	H	2	M	O
DE80	1	M	1	L	O
DE91	0	L	1	L	O
DE92	1	M	1	L	O
DE93	0	L	1	L	O
DE94	2	H	2	M	O
DEA1	1	M	1	L	O
DEA2	3	H	1	L	O
DEA3	3	H	3	H	A
DEA4	3	H	0	L	O
DEA5	1	M	2	M	A
DEB1	2	H	1	L	O
DEB2	0	L	1	L	O
DEB3	0	L	0	L	O
DEC0	0	L	1	L	O
DED2	3	H	3	H	A

(continued)

Table A3. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
DED4	2	H	0	L	O
DED5	0	L	3	H	B
DEE0	0	L	3	H	B
DEF0	1	M	2	M	A
DEG0	1	M	4	H	B
DK01	1	M	0	L	O
DK02	0	L	0	L	O
DK03	0	L	0	L	O
DK04	0	L	0	L	O
DK05	0	L	1	L	O
EL11	1	M	3	H	B
EL12	1	M	4	H	B
EL13	1	M	0	L	O
EL14	0	L	3	H	B
EL21	0	L	0	L	O
EL22	0	L	0	L	O
EL23	0	L	1	L	O
EL24	2	H	3	H	A
EL25	0	L	2	M	O
EL30	3	H	6	H	A
EL41	0	L	1	L	O
EL42	0	L	0	L	O
EL43	0	L	0	L	O
ES11	1	M	0	L	O
ES12	0	L	2	M	O
ES13	0	L	0	L	O
ES21	0	L	4	H	B
ES22	0	L	1	L	O
ES23	0	L	1	L	O
ES24	0	L	2	M	O
ES30	1	M	1	L	O
ES41	0	L	2	M	O
ES42	6	H	2	M	O
ES43	1	M	0	L	O
ES51	1	M	1	L	O
ES52	2	H	0	L	O
ES53	0	L	0	L	O
ES61	0	L	1	L	O
ES62	2	H	2	M	O
FR10	0	L	0	L	O
FR21	0	L	0	L	O
FR22	0	L	0	L	O
FR23	1	M	1	L	O
FR24	2	H	1	L	O
FR25	1	M	0	L	O
FR26	2	H	1	L	O
FR30	1	M	2	M	A
FR41	0	L	2	M	O
FR42	3	H	3	H	A
FR43	1	M	0	L	O

(continued)

Table A3. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
FR51	2	H	2	M	O
FR52	0	L	2	M	O
FR53	0	L	1	L	O
FR61	1	M	1	L	O
FR62	0	L	0	L	O
FR63	0	L	0	L	O
FR71	1	M	0	L	O
FR72	0	L	0	L	O
FR81	1	M	0	L	O
FR82	1	M	0	L	O
FR83	0	L	0	L	O
ITC1	1	M	0	L	O
ITC2	0	L	0	L	O
ITC3	1	M	0	L	O
ITC4	0	L	4	H	B
ITF1	0	L	3	H	B
ITF2	0	L	1	L	O
ITF3	1	M	1	L	O
ITF4	0	L	0	L	O
ITF5	1	M	0	L	O
ITF6	2	H	0	L	O
ITG1	1	M	3	H	B
ITG2	1	M	1	L	O
ITH1	1	M	1	L	O
ITH2	1	M	1	L	O
ITH3	3	H	1	L	O
ITH4	0	L	4	H	B
ITH5	1	M	2	M	A
ITI1	2	H	4	H	A
ITI2	3	H	1	L	O
ITI3	3	H	1	L	O
ITI4	2	H	0	L	O
NL11	1	M	0	L	O
NL12	0	L	0	L	O
NL13	0	L	0	L	O
NL21	2	H	1	L	O
NL22	4	H	0	L	O
NL23	1	M	0	L	O
NL31	0	L	1	L	O
NL32	0	L	7	H	B
NL33	3	H	1	L	O
NL34	0	L	2	M	O
NL41	2	H	1	L	O
NL42	2	H	1	L	O
PL11	2	H	5	H	A
PL12	4	H	4	H	A
PL21	5	H	5	H	A
PL22	1	M	6	H	B
PL31	3	H	1	L	O
PL32	2	H	1	L	O

(continued)

Table A3. Continued

Regions	2004–2008		2008–2012		Resilient type
	Entry number	Rank group	Entry number	Rank group	
PL33	0	L	0	L	O
PL34	3	H	1	L	O
PL41	1	M	8	H	B
PL42	2	H	4	H	A
PL43	1	M	0	L	O
PL51	2	H	2	M	O
PL52	2	H	2	M	O
PL61	5	H	5	H	A
PL62	1	M	0	L	O
PL63	3	H	5	H	A
PT11	0	L	0	L	O
PT15	0	L	0	L	O
PT16	1	M	2	M	A
PT17	2	H	4	H	A
PT18	0	L	2	M	O
RO11	1	M	0	L	O
RO12	5	H	3	H	A
RO21	2	H	2	M	O
RO22	5	H	2	M	O
RO31	3	H	5	H	A
RO32	5	H	2	M	O
RO41	2	H	1	L	O
RO42	1	M	2	M	A

Note: Rank groups "L," "M," and "H" refer to "Low," "Medium," and "High," respectively. Resilient Type "A" refers to resilient regions that remain in the high/medium rank groups; resilient Type "B" refers to resilient regions that transit from the low/medium rank groups (2004–2008) to the high rank group (2008–2012); and resilient Type "O" refers to other regions.

Table A4. Description and summary statistics of main variables

Variables	Description	Observation	Mean	Median	Standard deviation	Minimum	Maximum
Entry_04-08	Entry number of all sectors for 2004–2008	173	2.39	2.00	2.18	0	10
Entry_HKI_04-08	Entry number of HKI sectors for 2004–2008	173	0.86	1.00	1.04	0	5
Entry_LKI_04-08	Entry number of LKI sectors for 2004–2008	173	1.21	1.00	1.39	0	7
Entry_08-12	Entry number of all sectors for 2008–2012	173	2.85	2.00	2.83	0	17
Entry_HKI_08-12	Entry number of HKI sectors for 2008–2012	173	0.99	0.00	1.65	0	13
Entry_LKI_08-12	Entry number of LKI sectors for 2008–2012	173	1.46	1.00	1.57	0	8
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 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 A5. Correlation coefficients among main variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Entry_04-08 (1)	1														
Entry_HKI_04-08 (2)	0.71	1													
Entry_LKI_04-08 (3)	0.83	0.29	1												
Entry_08-12 (4)	0.51	0.43	0.33	1											
Entry_HKI_08-12 (5)	0.39	0.38	0.22	0.79	1										
Entry_LKI_08-12 (6)	0.44	0.37	0.29	0.79	0.32	1									
RV (7)	0.29	0.26	0.23	0.36	0.22	0.38	1								
UV (8)	0.06	−0.07	0.07	0.01	0.02	−0.06	−0.37	1							
g4_gdppc (9)	0.49	0.35	0.39	0.33	0.25	0.29	0.07	0.13	1						
Los (10)	−0.25	−0.17	−0.21	−0.28	−0.17	−0.28	−0.74	−0.24	−0.15	1					
pop_den (log) (11)	0.12	0.16	0.06	0.19	0.27	0.07	−0.18	0.19	0.07	0.05	1				
GDP (log) (12)	−0.03	0.06	−0.08	0.11	0.17	0.01	0.10	0.13	−0.33	−0.08	0.56	1			
Share_S&T (log) (13)	−0.13	−0.03	−0.11	−0.02	0.11	−0.11	−0.19	0.12	−0.10	0.13	0.64	0.58	1		
Gross capital_emp (log) (14)	−0.56	−0.41	−0.45	−0.35	−0.24	−0.32	−0.31	0.09	−0.64	0.23	0.22	0.52	0.47	1	
EQI (15)	−0.35	−0.19	−0.29	−0.23	−0.09	−0.22	−0.14	−0.05	−0.26	0.15	0.27	0.43	0.56	0.56	1

Table A6. Probability of being resilient regions—robustness check based on probit model

Variable	Probit				
	All sectors			HKI sectors	LKI sectors
	Type A + Type B	Type A	Type B	Type B	Type A
RV	2.109***	1.927***	2.595***	2.330**	2.911***
	(0.556)	(0.612)	(0.750)	(1.091)	(0.827)
UV	0.934***	0.764**	1.274***	1.404*	1.144**
	(0.341)	(0.379)	(0.437)	(0.734)	(0.501)
g4_gdppc	−0.322	−0.526**	0.0192	−2.969***	−0.529
	(0.228)	(0.263)	(0.307)	(1.042)	(0.330)
Los	1.183***	1.037**	1.580***	1.411	1.857***
	(0.422)	(0.476)	(0.573)	(0.860)	(0.666)
pop_den (log)	0.377*	0.517**	−0.0491	1.040**	0.393
	(0.221)	(0.254)	(0.338)	(0.433)	(0.317)
GDP (log)	0.448*	0.424	0.764**	1.714**	0.618*
	(0.242)	(0.278)	(0.346)	(0.713)	(0.368)
Share_S&T (log)	−0.0757	0.0145	−0.0172	0.223	0.292
	(0.297)	(0.348)	(0.415)	(0.877)	(0.447)
Gross capital_emp (log)	−0.0150	0.0332	−0.273	−2.227**	−0.0628
	(0.370)	(0.381)	(0.558)	(1.062)	(0.462)
EQI	−0.151	0.0368	−0.267	−1.716**	0.220
	(0.274)	(0.303)	(0.394)	(0.840)	(0.393)
Constant	−0.809	−2.146***	−0.192	−0.479	−2.389***
	(0.620)	(0.825)	(0.752)	(0.919)	(0.867)
Country dummies	Yes	Yes	Yes	Yes	Yes
Observations	163	139	106	84	121
Pseudo R-squared	0.3195	0.3385	0.3394	0.5534	0.374
One-sided z tests on coefficients after estimation: H0: std_uv1 $\geq$ std_rv1	0.0000	0.0002	0.0006	0.0511	0.0001

Note: Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$. In Panel "Type A," Type B resilient regions are excluded. In Panel "Type B," Type A resilient regions are excluded.

Table A7. Probability of being resilient regions—robustness check based on OLS model

Variable	OLS				
	All sectors			HKI sectors	LKI sectors
	Type A + Type B	Type A	Type B	Type B	Type A
RV	0.489***	0.383***	0.407***	0.0754	0.352***
	(0.136)	(0.140)	(0.132)	(0.119)	(0.110)
UV	0.218**	0.146	0.203**	0.0527	0.147**
	(0.0919)	(0.0932)	(0.0921)	(0.0817)	(0.0687)
g4_gdppc	−0.0683	−0.0968	0.0134	−0.0739**	−0.0186
	(0.0607)	(0.0614)	(0.0493)	(0.0352)	(0.0508)
Los	0.281***	0.214**	0.252**	0.0353	0.219**
	(0.106)	(0.107)	(0.101)	(0.0891)	(0.0884)
pop_den (log)	0.0769	0.102	−0.0294	0.103*	0.0449
	(0.0692)	(0.0748)	(0.0638)	(0.0556)	(0.0434)
GDP (log)	0.112	0.0915	0.127*	0.0916	0.0263
	(0.0745)	(0.0797)	(0.0668)	(0.0620)	(0.0478)
Share_S&T (log)	0.000136	0.0190	0.0313	−0.0764	0.0377
	(0.0817)	(0.0896)	(0.0826)	(0.0550)	(0.0642)
Gross capital_emp (log)	−0.0103	−0.00924	−0.0379	0.0424	0.0138
	(0.126)	(0.129)	(0.124)	(0.0902)	(0.113)
EQI	−0.0367	−0.0136	−0.0451	−0.0678	0.0746
	(0.0799)	(0.0844)	(0.0919)	(0.0586)	(0.0621)
Constant	0.349**	0.112	0.402**	0.293*	0.0789
	(0.176)	(0.178)	(0.181)	(0.168)	(0.123)
Country dummies	Yes	Yes	Yes	Yes	Yes
Observations	163	139	114	128	147
R-squared	0.3351	0.3212	0.2802	0.3243	0.2754
One-sided *t* tests on coefficients after estimation: H0: std_uv1 ≤std_rv1	0.0001	0.0007	0.0012	0.3565	0.0008

Note: Robust standard errors in parentheses. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. In Panel "Type A," Type B resilient regions are excluded. In Panel "Type B," Type A resilient regions are excluded.