Competitiveness Review

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Received 17 December 2014
Revised 20 February 2015
Accepted 1 March 2015

Abstract

Purpose – The purpose of this study is to elucidate the determinants of economic resilience at various levels of analysis. While the economic benefits of regional clustering are well-documented, the impact of external shocks on regional clusters has only recently gained attention. This study explores the antecedents of economic resilience, defined as sustained employment growth, prior to and during the global financial crisis within the German biotechnology industry.

Design/methodology/approach – This study combines multilevel linear regression analysis with egocentric network analysis. This allows us to distinguish micro- and context-level effects in the analysis of economic resilience.

Findings – The findings of this study indicate that while specialization at the network and context-level is conducive to firm growth prior to the crisis, these configurations seem to be particularly susceptible to external shocks. Conversely, diversity (diversified regional agglomerations and diverse networks) seems to be associated with economic resilience during the crisis. Moreover, we find that economic resilience is connected to adaptive capability at the micro-level, that is, the ability to expand and diversify a firms' portfolio of network ties in the face of an external shock. Finally, we show that these adaptive processes are facilitated by geographical proximity among collaborating organizations.

Originality/value – This study contributes to the existing literature by showing that the antecedents of economic resilience are located at multiple levels of analysis. An important implication of this study is that the examination of the resilience of regional clusters may thus be significantly enhanced by disentangling effects at the firm, network and regional (i.e. context) level.

Keywords Resilience, Networks, Employment performance, External shocks, Multilevel analysis, Regional clusters

Paper type Research paper

1. Introduction

While the recent global financial crisis caused a severe downturn of economic activity across a wide range of economic systems, the impact of this external shock differed widely across sectors and regions. Uncertainties over market conditions and reduced liquidity in the financial system dramatically altered the competitive environment within high-technology industries, where access to venture capital is crucial (Gompers and Lerner, 2004; OECD, 2012). Moreover, it is well documented that high-technology industries – such as the biotechnology industry – tend to cluster in particular locations (Porter, 1998; Swann *et al.*, 1998). Geographically bounded knowledge spillovers, specialized labor pools as well as intensive local

Competitiveness Review
Vol. 25 No. 4, 2015
pp. 371-391

1059-5422
DOI 10.1108/CR-12-2014-0038

competition have been identified as important drivers of regional clustering giving rise to innovation, employment as well as productivity growth (Baptista and Swann, 1998; Delgado *et al.*, 2010; Jaffe *et al.*, 1993; Porter, 1998). However, while the benefits of the spatial concentration of economic activity are well-documented, the ways in which regional clusters as well as the firms representing a cluster's main constituent components respond to external shocks has only recently gained attention under the umbrella concept of "economic resilience" (Martin and Sunley, 2011; Martin, 2012; Pendall *et al.*, 2010; Wrobel, 2013). More generally, the question whether regional clusters promote or inhibit economic resilience has not been addressed sufficiently. It has been argued that economic resilience is associated with a cluster's capacity to adapt in the face of external shocks (Pendall *et al.*, 2010; Simmie and Martin, 2010). Moreover, recent studies suggest that a cluster's adaptive capacity is determined by its constituent components, that is, its firms (Menzel and Fornahl, 2010). A large body of literature has shown that firm performance, in turn, depends on the ability to adapt to and exploit changes in the business environment. In this context, firms face a fundamental trade-off between explorative and exploitative adaptation (March, 1991). The ways in which firms balance exploration and exploitation may thus have an important influence on economic resilience at the firm and regional levels.

The recent global financial crisis represents an external shock which allows us to study the relationship between economic resilience and regional clusters. At the same time, this provides us with the rare opportunity to extend the examination of regional clusters to its constituent components, which is of particular importance given that a cluster's response to an external shock is defined by firms (Holm and Ostergaard, 2013; Martin and Sunley, 2011; Menzel and Fornahl, 2010; Wrobel, 2013). An important starting point of this paper is that the antecedents of economic resilience are located at multiple levels of analysis. While extant research has tended to examine economic resilience at the regional level, we posit that this may considerably underestimate heterogeneity at lower-order levels of analysis. At the firm-level, external shocks may erode competitive positions, which is why in the face of changing environmental circumstances firms must seek to adapt accordingly. Moreover, firms are not isolated from their regional environment. That is, economic resilience may be supported (or inhibited) by different context-level features concerning, for instance, location within a cluster as well as the economic structure of regional clusters.

Our empirical multilevel framework allows us to disentangle micro-level effects from context-level features (pertaining to the regional environment in which firms are embedded). Moreover, we examine the impact of changing environmental conditions in two temporal brackets that delineate two phases of homogeneous environmental conditions (i.e. *pre-crisis* and *crisis*).

The remainder of this paper is structured as follows. Section 2 summarizes the theoretical background. Section 3 presents the data and methods. The results are reported in Section 4. Section 5 concludes this paper.

2. Literature background and hypotheses

2.1 Economic resilience and regional clusters

In the wake of the recent global financial crisis, scholarly interest has increasingly focused on the resilience of regional economies and regional clusters. While it has been shown that firms in regional clusters, that is, "geographical concentrations of interconnected companies […] in a particular field" (Porter, 1998, p. 197), outperform non-clustered firms in terms of growth (Beaudry and Schiffauerova, 2009), as well as innovation and productivity growth (Baptista and Swann, 1998; Porter, 1998), the performance implications of regional clusters during economic crises remain unclear. Under the umbrella concept of "economic resilience", recent studies have addressed the role of changing environmental conditions and regional clustering (Wrobel, 2013). An important starting point was the observation that while a large range of clusters was adversely affected by external shocks, some clusters successfully navigated discontinuities in the external environment, thus proving to be resilient. Economic resilience may be defined as the "ability […] to recover successfully from shocks" (Hill *et al.*, 2008, p. 4). More specifically, economic resilience relates to the capacity of a regional economy or regional cluster to adapt its structure – a process that is referred to as "industrial mutation" by Simmie and Martin (2010) – so as to *sustain* growth in output (Martin, 2012). Other conceptions of resilience have placed a slightly different focus on the *persistence* of social and ecological systems (pertaining to the magnitude a system can tolerate and still persist) (Adger, 2000)[1]. Empirical studies show that a cluster's vulnerability to external shocks and its ability to adapt depends on the capabilities as well as the network interactions of individual firms (Holm and Ostergaard, 2013; Wrobel, 2013). This study draws on related conceptual and empirical work that uses employment as a central variable of cluster evolution (Menzel and Fornahl, 2010) and the economic resilience of regional clusters (Wrobel, 2013). Employment performance gives an indication of economic resilience at the firm and cluster levels. On the one hand, external shocks may adversely affect a firms' competitive advantage and economic situation which is reflected in the level of employment of individual firms. On the other hand, employment losses may cause regional economies to enter into recessions. We define economic resilience as a firms' ability to sustain or augment employment performance during crisis as compared to a previous level of employment prior to the crisis. More specifically, in this paper, we examine economic resilience (defined as employment performance) in the context of an external shock in the form of the recent global financial crisis which led to the dramatic deterioration of venture capital availability in the years 2009-2010 (Ernst & Young, 2011) compared to the pre-crisis situation in 2007-2008.

2.2 Micro-level effects

It is widely acknowledged that sustained competitive advantage requires the deployment of resources and capabilities that are appropriate to a firms' external environment (Tushman and O'Reily, 2004). Although firm-internal considerations may prompt firms to change their strategy, changes may also be imposed upon firms by variations in the external environment. External shocks including the emergence of new technological paradigms, changes in regulation, market demand – or, in our case, capital market conditions – may give rise to discontinuities that trigger high degrees of uncertainty (Dess and Beard, 1984; Pfeffer and Salancik, 1978), as well as competence destruction (Tushman and Anderson, 1986), thus rendering former core-capabilities obsolete. This, in turn, has an important bearing on the economic situation of firms as well as the ways in which firms allocate resources.

In high-technology industries, inter-organizational networks represent one of the most widely dispersed forms of coordination providing access to various complementary resources such as financial and human capital, as well as technological capabilities and marketing skills (Ahuja, 2000; Burt, 1992). When engaging in inter-organizational networks, firms are confronted with a fundamental trade-off in the decision whether resources are allocated to the refinement of existing capabilities (exploitation) or to the discovery of new knowledge and capabilities (exploration) (Gilsing, 2005; Lavie and Rosenkopf, 2006; March, 1991). While exploitation relating to the efficient use and refinement of existing assets and capabilities is needed for survival in the short term, exploration, that is, the development of new capabilities is needed for long-term survival (Tushman and O'Reily, 2004). Balancing these activities poses a considerable trade-off for firms. In essence, this trade-off arises from the role of diversity and specialization in inter-organizational learning. While diversity, referring to the heterogeneity of partners or knowledge and cognitive distance within the network (Baum *et al.*, 2000; Koka and Prescott, 2002; Lavie and Rosenkopf, 2006; Rodan and Galunic, 2004), is a primary factor for the generation of Schumpeterian novel combinations (Nelson and Winter, 1982), it is also associated with important drawbacks. Although diversity increases the potential for innovative outcomes (Koka and Prescott, 2002), organizations are limited in their capacity to assimilate and make use of novel knowledge as firms need to learn how to bridge cognitive distances (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998). By contrast, the refinement of existing capabilities and resources (i.e. exploitation) is associated with short-term efficiency, as absorptive capacity and cognitive proximity facilitate inter-organizational learning. Exploitation has been observed in industry environments characterized by low uncertainty and competence-enhancing technological change in which efficiency considerations are crucial. These regimes have been shown to promote specialization, that is, specific knowledge in a narrow range of issues (Gilsing, 2005). However, exploitation is also associated with risks, as specialization on a narrow range of issues may leave firms particularly exposed to environmental change (Levitt and March, 1988), whereas, in environments characterized by competency-destroying discontinuities, survival and growth may be associated with the need to gain access to new and diverse resources that are crucial for adaptation (explorative adaptation) (Tushman and O'Reily, 2004).

It has been shown that cognitive proximity between collaborating firms, which, for the purpose of this study, is defined as low partner diversity, is conducive to the efficient transfer of knowledge in inter-organizational networks (Boschma and Frenken, 2010; Sampson, 2007; Simonin, 1999). That is, common skills and related technological platforms facilitate knowledge transfer and cumulative specialization by reducing the costs and time needed for the assimilation and economic use of external knowledge (Cohen and Levinthal, 1990; Kahl, 2014; Lane and Lubatkin, 1998). We thus assume that firms engaged in networks with low partner diversity will focus on exploitation (Rothaermel and Deeds, 2004), which we assume to be positively associated with firm growth in the competency-enhancing regime prior to the crisis. By contrast, in inter-organizational networks involving a high degree of diverse agents with heterogeneous knowledge bases, firms need to develop an in-depth understanding of a broad variety of technological fields which may be associated with inefficiency and higher costs (Cohen and Levinthal, 1989; Gilsing, 2005; Lane and Lubatkin, 1998; Sampson, 2007; Simonin, 1999):

H1. Network diversity will be negatively associated with employment performance prior to the crisis.

However, while cognitive proximity among network ties enables efficient knowledge transfer, it may not be sufficient to stimulate innovative resource combinations (Ahuja, 2000; Noteboom, 2000). Empirical studies suggest that exploration is particularly important in changing environments (Gilsing, 2005) because gaining access to new and diverse resources provides the flexibility needed to respond to external shocks (Boschma and Frenken, 2010; Fleming, 2001). We thus assume that network diversity is positively associated with firm growth during the crisis:

H2. Network diversity will be positively associated with employment performance during the crisis.

Inter-organizational networks are characterized by a specific geography. Recent studies suggest that geographical proximity among collaborating firms is neither a necessary nor a sufficient condition for innovation (Boschma and Frenken, 2010; Boschma, 2005). Rather than geographical proximity, it has been argued that various forms of proximity among network partners matter for performance and innovation (Boschma, 2005; Capaldo and Petruzzelli, 2014). Therefore, we do not expect the geography of network ties *per se* to influence firm growth prior to the crisis:

H3. The geography of network ties will have no influence on employment performance prior to the crisis.

By contrast, in environments characterized by competence-destroying change and uncertainty, firm growth may be associated with regional interactions. In contrast to extra-regional linkages, the transactions costs for the identification of collaboration partners, as well as the costs arising from collaboration and monitoring activities, are substantially lower within geographical proximity (Cooke, 2001; Marzucchi *et al.*, 2013). Moreover, face-to-face interactions may facilitate the development of shared trust among collaboration partners. Uncertainty reduction and efficiency gains derived from regional networking may thus be particularly important to resolve the conundrum arising from the need for exploration in times of crisis – as both exploration and economic crises are characterized by high degrees of uncertainty:

H4. Regional networks will be positively associated with employment performance during the crisis.

2.3 Context-level effects

Firms are embedded in a specific regional economic context beyond their immediate portfolio of network ties (Cooke, 2001). Importantly, the clustering of economic activity has been shown to exert context-effects which are crucial for firm growth, productivity and innovation (Beaudry and Schiffauerova, 2009; Porter, 1990, 1998). However, less scholarly attention has been on the relationship between changing external conditions and regional clustering.

Two broad categories of cluster externalities associated with the process of knowledge creation and diffusion may be distinguished. One the one hand, this relates to localization economies, which are stimulated by regional industry specialization or the strength of the industry within a particular region (Baptista and Swann, 1999). The benefits derived from regional clustering of industries is attributed to knowledge spillovers (Jaffe *et al.*, 1993; Glaeser *et al.*, 1992), reduced transport costs for inputs and outputs, as well as specialized labor markets. More specifically, the concentration of an industry within a region is associated with Marshall–Arrow–Romer externalities derived from intra-industry knowledge spillovers between firms. Specialization is thus assumed to promote the transmission and exchange of tacit and codified knowledge through imitation (Pouder and St. John, 1996) and inter-firm circulation of skilled workers as well as local competition among firms (Porter, 1990). On the other hand, Jacobs (1969) argues that the most important source of knowledge spillovers and innovation is diversity. Urbanization economies arise from large functional agglomerations as well as industry variety within a region. In this line of argumentation, diverse regional economic structure is associated with higher opportunities for search and experimentation as well as for the recombination of resources and capabilities across industries (Beaudry and Schiffauerova, 2009).

While empirical studies report on a positive relationship between firm growth and localization (Baptista and Swann, 1998), as well as urbanization economies (Beaudry and Swann, 2009), Neffke *et al.* (2011) find that these effects vary across the industry life cycle. Drawing on these studies, we expect the benefits derived from regional economic structure to vary across different environmental conditions. In stable and competence-enhancing environments, we expect specialized regional clusters of biotechnology firms to be associated with firm growth. In these environments, we posit that cumulative regional specialization will foster absorptive capacity and intra-industry knowledge spillovers which, in turn, facilitate firm growth:

H5. Localization economies will be positively associated with employment performance prior to the crisis.

By contrast, competence-destroying discontinuities may place pronounced constraints on firms located in narrowly specialized clusters due to established routines and high restructuring costs. These types of clusters may be particularly vulnerable to external shocks (Grabher, 1993). Narrow specialization may thus impede a cluster's adaptability in the face of changing environmental conditions thereby undermining the resilience of the firms in the cluster:

H6. Localization economies will be negatively associated with employment performance during the crisis.

Recent empirical studies suggest that the diversity of the economic structure of a cluster promotes economic resilience (Holm and Ostergaard, 2013; Wrobel, 2013). We thus assume that urbanization economies are associated with employment growth in competence-destroying environments. In essence, diversified regional clusters may succeed at spreading risk associated with external shocks across various industries. Moreover, the varied stock of resources available in diversified regional agglomerations may enable firms to flexibly recombine a broad set of resources which, in turn, may promote adaptation in the face of an external shock:

H7. Urbanization economies will be positively associated with employment performance during the crisis.

3. Methods and data

3.1 Structure of the empirical model

In this section, we present the structure of our empirical model. This paper combines egocentric network (Wasserman and Faust, 1994) and multilevel analysis (Raudenbush and Bryk, 2002) in two separate sets of models (*pre-crisis* and *crisis*). To capture the effect of the external shock represented by the global financial crisis, we distinguish two temporal brackets of homogeneous environmental conditions, that is, *pre-crisis* including the years 2007-2008 characterized by relative stability and capital market munificence, on the one hand, and *crisis* marked by competency-destroying change, uncertainty and the deterioration of capital market conditions in the years 2009-2010 on the other.

Choosing a multilevel approach allows us to reflect an important part of (economic) reality inasmuch as firms are not isolated from their environment but nested within a specific regional economic and institutional context (Luke, 2004; Snijders and Bosker, 2004). In addition, high-technology firms are commonly embedded in a broad set of inter-organizational relationships. Using egocentric network analysis allows one to capture the effects of a focal firms' portfolio of inter-organizational ties on employment performance.

We gauge the impact of five firm- (X^1-X^5), four network-related (X^6-X^9) and two context-level predictors (R^1-R^2) on employment performance (Y) in the German biotechnology industry. We use the statistics program "HLM 7" from Raudenbush *et al.* (2011) for the model estimates. A formal notation of this two-level linear regression model is provided below:

$$\mathbf{Y_{ij}} = [\boldsymbol{\delta}^{00} + \boldsymbol{\delta}^{10}\mathbf{X_{ij}} + \boldsymbol{\delta}^{01}\mathbf{R_j} + [\mathbf{u_j} + \mathbf{r_{ij}}]$$

with,

Y_{ij} = Response variable at the firm level.

Employment growth (in per cent):

δ^{00} = Regression intercept;
X_{ij}^{a} = Explanatory variables at the firm level;
X_{ij}^{1} = *Product*; X_{ij}^{2}: *Product orientation*; X_{ij}^{3}: *Service*; X_{ij}^{4}: *Servitization*; X_{ij}^{5}: *Firm size*; X_{ij}^{6}: *Network diversity*; X_{ij}^{7}: *Network regional*; X_{ij}^{8}: *Network size*; and X_{ij}^{9}: *Network churn*;
R_j^{b} = explanatory variables at the context level;
R_j^{1} = Concentration;
R_j^{2} = Population density;
$R_{ij;}\ u_j$ = Error terms of the firm (r) and the regional level (u).

The structure of the model is strictly hierarchical in the sense that i biotech firms are nested in j regions. As suggested by Hox (2010), we chose a bottom-up strategy consisting of six consecutive analytical steps to construct our models. We first estimated the impact of our five firm- (Column 1) and four network-related predictors (Column 2), separately. We then excluded the highly insignificant variables (p-value $\geq$ 0.20) and merged the remaining micro-level predictors in a joint model (Column 3). We then controlled for the two context-level predictors (Column 4) and finally, to test the robustness of our results, we added four control variables covering the regional economic capacity (Column 5) and the regional labor market (Column 6), respectively. As expected, we observe an improving model fit (documented by declining deviance values) as more predictor variables are included.

3.2 Sample

The data for the response variable as well as for the firm and network predictors are derived from the German Biotechnology Year and Address Book (BIOCOM) for the years 2007 to 2010. For the purpose of this paper, BIOCOM data provide at least three advantages. First, it represents the most comprehensive independent repository of the German biotechnology industry with a response rate of approximately 80 per cent. This enabled us to identify 266 biotechnology firms in both brackets representing approximately 50 per cent of the population of German biotechnology firms. Second, the database reports micro-data including location, year of establishment, business models and employment as well as network partners of individual firms. The database is thus amenable to multilevel analysis allowing us to capture the hierarchical relationship between the firm and its regional context. Third, the database reports longitudinal data which allows us to construct a panel of two-year temporal brackets (*pre-crisis* and *crisis*) comprising 266 biotechnology firms. Moreover, even though employment losses were significant in the German biotechnology industry, a negligible number of exits was observed (Ernst & Young, 2012), thus reducing sample bias. Finally, for the predictors at the context-level, we draw on EUROSTAT data.

3.3 Variables

For our response variable at the micro-level *Employment Performance* (Y_{ij}), used as a proxy for economic resilience (Wrobel, 2013; Baptista and Swann, 1999), we first compute the within-bracket mean employment of individual biotechnology firms and subsequently gauge the cross-bracket employment growth (in per cent). We specify five network-related explanatory variables. *Network Size* (${X_{ij}}^2$), *Network Churn* (${X_{ij}}^3$), *Network Diversity* (${X_{ij}}^4$) and *Network Regional* (${X_{ij}}^5$). *Network Size* (${X_{ij}}^2$) captures a focal firm's number of direct ties. Linked to that, we define *Network Churn* (${X_{ij}}^3$) as the growth rate of *Network Size* across the brackets identified above. The fourth predictor, i.e. *Network Diversity* ${X_{ij}}^4$, is based on the Blau Index (Blau, 1977) that captures the diversity of a firms' portfolio of network ties. To compute network diversity, in line with Powell *et al.* (2005), we first identify five categories of partner organizations including biotechnology firms, public research organizations, pharmaceutical corporations and government institutes, as well as biomedical companies. We then compute the Blau Index, a measure commonly used to gauge network diversity, for individual biotechnology firms:

$$\textbf{Blau's index}\, d = 1 - \sum\nolimits_{i=1}^{n} p_i^2$$

N represents the total number of categories of network partners and *p* computes the percentage of objects in a certain category. This measures ranges from 0 to 1, where 0 represents completely homogeneous networks and 1 completely diversified networks. If a firm has a wide range of network partners, the measure will be high (1 or close to 1), whereas if most collaboration partners are concentrated in a specific category, it will be low. Finally, *Network Regional* (X_{ij}^5) captures the share of regional network ties within a focal firms' portfolio of network ties. To construct this measure, we coded the geographical localization of all network ties in different geographical categories (regional, national, international and global). Collaborations within the same federal state were classified as "regional". All collaborations with German network partners were defined as "national", whereas collaborations with European partners and non-European partners were assigned "international" and "global", respectively.

At the context-level, we distinguish two predictors, that is, *Concentration* (R_j^1) and *Population Density* (R_j^2). *Concentration* (R_j^1) computes the degree of disproportionality of the spatial distribution of the German biotechnology industry in relation to a national reference. We assess the share of biotechnology firms within NUTS-2 regions in relation to the number of biotechnology firms at the national level. This variable is used as a proxy for localization economies. *Population Density* (R_j^2) computes population density in NUTS-2 regions (number of inhabitants per square kilometer) and serves as a proxy for urbanization economies.

Moreover, several control variables were used. We controlled for *Firm Size* relating to the absolute number of employees (in *t*–1) and for *Network Size*, several business models as well as business model adaptation. At the regional-level we controlled for *Log Regional GDP per Capita* and the share of *Regional Unemployment* as well as for the change in *Regional GDP* and *Regional Unemployment* at the NUTS-2 level across the brackets identified above.

4. Results

4.1 Descriptive results

Tables II-V present the descriptive results of our empirical analysis including means, standard deviations and correlations. None of the correlations between the predictor variables indicates multicollinearity. All micro-level predictors were estimated for the years 2007-2010 for 266 firms. During the crisis, we observe a sharp decline in *employment growth*, as well as a lower standard deviation. Although total employment growth remains positive, it is the result of fewer firms. During the crisis, we observe increasing *Firm Size* (in t−1). This is attributable to growth in the *Pre-Crisis* model. While average *Network Size* is slightly higher in the *Crisis*-model, *Network Churn* is reduced during *crisis*. Moreover, the means for *Network Diversity* and *Network Regional* are relatively stable in both models. At the context-level, all predictors were estimated for 34 NUTS-2 regions. We observe the impact of the global financial crisis as evidenced by the decline of *Regional GDP Per Capita* in the *Crisis*-model. Interestingly enough, prior to the impact on regional GDP, as well as employment in the biotechnology industry, we observe an increase in *Unemployment* in the *Pre-Crisis* model. High standard deviation indicates that this varied considerably across NUTS-2 region (Tables I-IV).

Table I.
Variable means, standard deviations and correlations (*Pre-Crisis*; micro-level)[a]

Variable	Mean	SD	Y	X^1	X^2	X^3	X^4	X^5	X^6	X^7	X^8	X^9
Y: Empl_Performance	27.34	65.03	1	−0.01	−0.05	−0.06	0.17**	0.09	−0.06	−0.08	0.09	0.12*
X^1: Product	0.23	0.42	−0.01	1	0.04	−0.26**	0.28**	0.10	−0.13*	−0.11	−0.08	−0.06
X^2: Product orientation	0.20	0.40	−0.05	0.04	1	−0.23**	−0.27**	0.02	0.02	0.14*	0.07	−0.04
X^3: Service	0.18	0.39	−0.06	−0.26**	−0.23**	1	−0.12	−0.11	−0.04	0.00	−0.04	0.08
X^4: Servitization	0.23	0.42	0.17**	−0.28**	−0.27**	−0.12	1	0.01	−0.01	−0.03	0.06	0.05
X^5: Firm size (in $t-1$)	44.23	133.74	0.09	0.10	0.02	−0.11	0.01	1	−0.08	−0.16**	0.04	−0.10
X^6: Network diversity	0.37	0.25	−0.06	−0.13*	0.02	−0.04	−0.01	−0.08	1	−0.15*	0.43**	0.20**
X^7: Network regional	35.41	34.26	−0.08	−0.11	0.14*	0.00	−0.03	−0.16**	−0.15*	1	−0.22**	0.02
X^8: Network size	5.64	4.97	0.09	−0.08	0.07	−0.04	0.06	0.04	0.43**	−0.22**	1	0.11
X^9: Network churn	25.28	69.08	0.12*	−0.06	−0.04	0.08	0.05	−0.10	0.20**	0.02	0.11	1

Notes: [a] n = 266; $*p \leq 0.05$; $**p \leq 0.01$

4.2 Regression results

The results of the linear multilevel regressions are presented in Tables V (*pre-crisis*) and VI (*crisis*). The results obtained here provide support for *H1* and *H2* relating to the effects of network structure on *Employment Performance*. Prior to the crisis, we observe a negative effect of *Network Diversity* and, conversely, a positive impact of specialization. By contrast, during the crisis, we report on a positive effect of *Network Diversity*. These observations may be explained by the exploitation–exploration framework. While specialized network structures with high degrees of cognitive proximity have been shown to be conducive to the efficient use and exploitation of external knowledge (Boschma and Frenken, 2010), these network structures may not be sufficient to stimulate new resource combinations that facilitate adaptation during crisis. Economic resilience thus seems to be connected to diverse inter-organizational networks.

Moreover, we provide support for *H3* and *H4* relating to the role of regional network ties during the crisis. While regional network ties had no effect on *Employment Performance* prior to the crisis, they gain importance in the face of an external shock. More specifically, *H3* provides support to the view that geographical proximity among network partners is neither a necessary nor a sufficient condition for positive network outcomes (Boschma, 2005). However, in line with *H4*, this only seems to hold for relatively stable environmental conditions. By contrast, during crisis regional network ties gain significance in facilitating *Employment Performance*. This seems to indicate the importance of face-to-face interactions and shared trust among organizations in the biotechnology industry which may be particularly relevant for the effective reconfiguration of inter-organizational networks as well as for dealing with high levels of uncertainty induced by changing environmental conditions.

Consistent with *H5*, we report positive localization effects at the context-level before the crisis. Moreover, in line with *H7*, urbanization economies are positively associated with *Employment Performance* during the crisis. Finally, our results provide support for *H6*, i.e. specialized regional clusters are negatively related to *Employment Performance* during the crisis. The results reported here thus seem to indicate that the benefits derived from regional clusters are moderated by the state of the external environment. Although regional specialization seems to be conducive to employment growth in relatively stable and competence-enhancing environments (*H5*), regional specialization is associated with risks. That is, as clustered firms follow existing routines and technological capabilities in a process of cumulative

Variable	Mean	SD	R^1	R^2	C^1	C^2	C^3	C^4
R^1: Concentration	2.87	2.82	1	0.39*	0.33	−0.16	0.03	0.12
R^2: Population density	0.47	0.75	0.39*	1	0.39*	−0.14	0.27	0.26
C^1: Log GDP per capita	10.25	0.23	0.33	0.39*	1	−0.45**	–	–
C^2: Δ GDP per capita	8.27	1.66	−0.16	−0.14	−0.45**	1	–	–
C^3: Unemployment	8.41	3.65	0.03	0.27	–	–	1	0.51**
C4: Δ Unemployment	−2.52	5.41	0.12	0.26	–	–	0.51**	1

Notes: [a] n = 34; $*p \leq 0.05$; $**p \leq 0.01$

Table II. Variable means, standard deviations and correlations (*Pre-Crisis*; context-level)[a]

Table III.
Variable means, standard deviations and correlations (*Crisis*; micro-level)[a]

Variable	Mean	SD	Y	X^1	X^2	X^3	X^4	X^5	X^6	X^7	X^8	X^9
Y: Empl_Performance	10.96	45.24	1	−0.03	0.01	0.07	−0.04	−0.05	0.11	0.09	0.04	0.11
X^1: Product	0.28	0.45	−0.03	1	−0.01	−0.36**	−0.27**	0.03	−0.13*	−0.14*	−0.13*	−0.08
X^2: Product orientation	0.22	0.42	0.01	−0.01	1	−0.22**	−0.23**	−0.02	0.08	−0.07	0.09	0.13*
X^3: Service	0.24	0.43	0.07	−0.36**	−0.22**	1	0.06	−0.09	−0.01	0.09	−0.13*	−0.03
X^4: Servitization	0.16	0.37	−0.04	−0.27**	−0.23**	0.06	1	0.06	0.02	0.01	0.02	−0.03
X^5: Firm size (in t−1)	63.66	251.07	−0.05	0.03	−0.02	−0.09	0.06	1	−0.08	−0.14*	0.09	0.02
X^6: Network diversity	0.38	0.26	0.11	−0.13*	0.08	−0.01	0.02	−0.08	1	−0.09	0.42**	0.11
X^7: Network regional	34.80	34.15	0.09	−0.14*	−0.07	0.09	0.01	−0.14*	−0.09	1	−0.18**	−0.10
X^8: Network size	6.13	5.48	0.04	−0.13*	0.09	−0.13*	0.02	0.09	0.42**	−0.18**	1	0.24**
X^9: Network churn	18.79	69.48	0.11	−0.08	0.13*	−0.03	−0.03	0.02	0.11	−0.10	0.24**	1

Notes: [a] n = 266; $*p \leq 0.05$; $**p \leq 0.01$

specialization, the barriers to new technologies, procedures and strategies become more pronounced. This in turn seems to render specialized regional clusters less equipped to react to changes in the external environment (*H6*). By contrast, diversified regional agglomerations seem to be particularly well equipped to withstand external shocks (*H7*). These types of clusters provide access to a diverse set of assets which may be critical for the flexible recombination of resources and adaptation in times of crisis.

Considering the lack of significance of the control variables pertaining to the type of business models and (nearly all variables related to) business model adaptation, rather than changing the architecture of the value creation, economic resilience seems to be associated with the restructuring of inter-organizational networks. Two control variables warrant further discussion. First, the results for the control variable *Servitization* which refers to business model changes from product-based business models to service-based business models indicate that while these types of business model changes were beneficial to *Employment Performance* prior to the crisis, during the crisis they had no effect. This is somewhat surprising given that service-based business models are associated with more short-term revenue generating potential as well as considerably lower capital requirements and risk – all of which are seemingly important during crisis. Second, the results for *Network Churn* relating to the growth rate of a focal firms' portfolio of network ties indicate a positive effect prior to and during the crisis. The expansion and renewal of networks and thus access to a larger set of resources seems to be beneficial to *Employment Performance*, irrespective of the nature of the business environment. However, the results reported above relating to the varying effects of network structure provide a more nuanced picture. It may thus be inferred that while prior to the crisis the expansion of networks in terms of specialization supports *Employment Performance*, during the crisis diversification fosters economic resilience (Tables V and VI).

5. Conclusion

The aim of this paper was to explore the economic resilience of regional clusters and firms in times of crisis. This study contributes to the existing literature by showing that the antecedents of economic resilience are located at multiple levels of analysis. An important implication of this study is that the examination of the resilience of regional clusters may thus be significantly enhanced by disentangling effects at the firm, network and regional (i.e. context) levels.

Variable	Mean	SD	R^1	R^2	C^1	C^2	C^3	C^4
R^1: Concentration	2.87	2.82	1	0.39*	0.35*	0.05	0.04	0.07
R^2: Population density	0.47	0.75	0.39*	1	0.42*	0.00	0.29	−0.17
C^1: Log GDP per capita	10.25	0.22	0.35*	0.42*	1	−0.52**	–	–
C^2: Δ GDP per capita	−0.02	2.46	0.05	0.00	−0.52**	1	–	–
C^3: Unemployment	7.60	2.70	0.04	0.29	–	–	1	−0.67**
C^4: Δ Unemployment	−0.65	9.59	0.07	−0.17	–	–	−0.67**	1

Notes: [a]n = 34; $*p \leq 0.05$, $**p \leq 0.01$

Table IV. Variable means, standard deviations and correlations (*Crisis*; context-level)[a]

Table V. Regression results (*Pre-Crisis*) (with robust standard errors)[ab]

Response variable: firm growth (%)	Firm-related variables (X^1-X^5) Coefficient (standard errors)	Network-related variables (X^6-X^9) Coefficient (Standard errors)	Firm- and network-related variables Coefficient (standard errors)	Regional context variables (R^1-R^2) Coefficient (standard errors)	Regional control variables (C^1-C^2) Coefficient (standard errors)	Regional control variables (C^3-C^4) Coefficient (standard errors)
Regression intercept	(+) 27.31*** (3.35)	(+) 27.31*** (3.25)	(+) 27.29*** (3.43)	(+) 23.58*** (3.81)	(+) 21.08*** (2.99)	(+) 23.73*** (3.81)
X^1: Product	(+) 3.18 (6.25)					
X^2: Product orientation	(−) 2.36 (7.57)					
X^3: Service	(−) 5.44 (6.08)					
X^4: Servitization	(+) 25.75** (10.33)		(+) 23.45** (10.19)	(+) 24.44** (10.60)	(+) 21.47** (10.90)	(+) 24.77** (10.68)
X^5: Firm size (in t−1)	(+) 0.04 (0.04)					
X^6: Network diversity		(−) 39.44** (16.71)	(−) 37.40** (17.13)	(−) 37.93** (16.61)	(−) 37.09** (16.42)	(−) 37.99** (16.72)
X^7: Network regional		(−) 0.16**** (0.12)	(−) 0.15 (0.12)			
X^8: Network size		(+) 1.63* (0.85)	(+) 1.49* (0.85)	(+) 1.81** (0.76)	(+) 1.66** (0.71)	(+) 1.76** (0.83)
X^9: Network churn		(+) 0.14**** (0.09)	(+) 0.13**** (0.08)	(+) 0.12**** (0.08)	(+) 0.12**** (0.08)	(+) 0.12**** (0.08)
R^1: Concentration				(+) 1.23** (0.46)	(+) 1.48*** (0.52)	(+) 1.29*** (0.44)
R^2: Population density				(+) 0.39 (1.20)		
C^1: GDP pc (ln)					(+) 42.38** (15.79)	
C^2: Δ GDP pc (%)					(+) 7.33*** (1.77)	
C^3: Unemployment						(+) 0.28 (0.87)
C^4: Δ Unemployment (%)						(−) 0.59 (0.68)
Level-1 –Variance	4,054.46	4,021.80	3,924.98	3,920.28	3,826.84	3,913.05
Level-2 –Variance	1.81	1.58	2.22	1.00	0.75	0.98
Deviance (null)	2,974.89	2,974.89	2,974.89	2,974.89	2,974.89	2,974.89
Deviance (model)	2,964.78**	2,962.61**	2,956.17***	2,955.77***	2,949.34***	2,955.28***

Notes: [a] $n = 266$; [b] all predictors are grand mean centered; spatial autocorrelation does not occur; the table displays unstandardized coefficients and standard errors; *** $p \leq 0.01$; ** $p \leq 0.05$; * $p \leq 0.10$; **** $p \leq 0.20$
Sources: BIOCOM AG ($N = 266$); EUROSTAT ($N = 34$), own calculations

Table VI. Regression results (*Crisis*) (with robust standard errors)[ab]

Response variable: firm growth (%)	Firm-related variables (X^1-X^5) Coefficient (Standard errors)	Network-related variables (X^6-X^9) Coefficient (Standard errors)	Firm- and network-related variables Coefficient (Standard errors)	Regional context variables (R^1-R^2) Coefficient (Standard errors)	Regional control variables (C^1-C^2) Coefficient (Standard errors)	Regional control variables (C^3-C^4) Coefficient (Standard errors)
Regression intercept	(+) 10.96*** (2.48)	(+) 10.95*** (2.68)	(+) 10.96*** (2.66)	(+) 10.97*** (2.12)	(+) 11.14*** (2.13)	(+) 11.05*** (1.84)
X^1: Product	(−) 1.71 (6.67)					
X^2: Product orientation	(+) 1.04 (9.34)					
X^3: Service	(+) 7.23 (7.20)					
X^4: Servitization	(−) 5.06 (7.55)					
X^5: Firm size (in t−1)	(−) 0.01** (0.01)		(−) 0.01* (0.003)	(−) 0.01**** (0.01)	(−) 0.01**** (0.01)	(−) 0.01**** (0.01)
X^6: Network diversity		(+) 19.31**** (13.94)	(+) 17.90* (10.73)	(+) 19.25* (11.13)	(+) 18.94* (11.19)	(+) 19.01* (11.22)
X^7: Network regional		(+) 0.14** (0.07)	(+) 0.14** (0.07)	(+) 0.13** (0.07)	(+) 0.13** (0.06)	(+) 0.13** (0.07)
X^8: Network size		(−) 0.11 (0.57)				
X^9: Network churn		(+) 0.08** (0.03)	(+) 0.08** (0.03)	(+) 0.08** (0.03)	(+) 0.08** (0.03)	(+) 0.08** (0.03)
R^1: Concentration				(−) 0.76*** (0.21)	(−) 1.14*** (0.40)	(−) 0.99*** (0.22)
R^2: Population density				(+) 5.89*** (0.43)	(+) 5.23*** (1.19)	(+) 7.69*** (1.13)
C^1: GDP pc (ln)					(+) 13.32 (11.27)	
C^2: Δ GDP pc (%)					(+) 0.95 (1.36)	
C^3: Unemployment						(−) 0.88 (0.92)
C^4: Δ Unemployment (%)						(+) 0.03 (0.36)
Level-1 –Variance	2,019.12	1,965.63	1,964.31	1,920.27	1,917.60	1,915.12
Level-2 –Variance	1.19	3.94	3.35	0.32	0.31	0.30
Deviance (null)	2,781.91	2,781.91	2,781.91	2,781.91	2,781.91	2,781.91
Deviance (model)	2,779.37	2,772.60*	2,772.34**	2,765.91**	2,765.54**	2,765.19**

Notes: [a] $n = 266$; [b] all predictors are grand mean centered. Spatial autocorrelation does not occur; the table displays unstandardized coefficients and standard errors; $^{***}p \leq 0.01$; $^{**}p \leq 0.05$; $^{*}p \leq 0.10$; $^{****}p \leq 0.20$

Sources: BIOCOM AG ($N = 266$); EUROSTAT ($N = 34$), own calculation

The following three main results are identified. First, while being located in a narrowly specialized cluster was shown to facilitate *Employment Performance* prior to the crisis, regional economic specialization seemed to undermine economic resilience in the face of an external shock. This may be explained by the process of cumulative specialization rendering these regional clusters particularly exposed to competency-destroying change, thus turning core competencies into core rigidities. Second, the results show that diversified regional agglomerations are associated with economic resilience. These regional clusters seem to provide a greater potential for the innovative recombination of resources and capabilities thus enabling local adaptive processes. Third, economic resilience is associated with micro-level adaptive capability, that is, a firms' ability to renew and reconfigure its portfolio of networks ties so as to increase the size and diversity in the face of changing environmental conditions. Moreover, these adaptive processes seem to be fostered by geographical proximity. Geographical proximity thus seems to resolve an important conundrum relating to the need for exploration in times of crisis. That is, both exploration and rapidly changing environments are characterized by uncertainty, which is why these activities may be particularly difficult in the face of an external shock. However, geographical proximity seems to reduce uncertainty among collaborating organizations and facilitate explorative adaptation.

The results obtained in this study have several implications for policymakers. The results pertaining to the economic resilience of regional clusters seem to reflect the exploration–exploitation trade-off identified at the micro-level relating to the conflicting nature of specialization and diversity. In reference to the notion of organizational ambidexterity (Tushman and O'Reily, 2004), sustainable cluster growth may thus entail balancing explorative and exploitative activities. Policymakers may thus choose to foster diversity by supporting new firm formation as well as launching cluster-oriented policies that promote local discovery and exploration processes in related, yet new fields to increase the resilience of regional clusters in anticipation of external shocks. Moreover, cluster management agencies may promote economic resilience by increasing diversity at the network-level through the provision of collaboration platforms and R&D-support schemes.

The results documented in this study also relate to a parallel discussion on organizational resilience which offers important insights in the proactive management of resilience. Two of our main results at the micro-level indicate that economic resilience is supported by adaptive capability and by the diversification of the portfolio of network ties. The organizational resilience literature (Lee *et al.*, 2013) shows that to engage in these restructuring processes, firms must develop planning strategies relating to the management of vulnerabilities within a firms' business environment. More specifically, economic resilience necessitates a proactive posture. Firms need to display a strategic and behavioral readiness reacting to early warning signals in an organizations' external environment. Firms also need to build an understanding of the resources and relationships they may need to build and access during crisis (Lee *et al.*, 2013; McManus *et al.*, 2008). Moreover, adaptive capability presupposes a range of factors and processes within the firm including the minimization of social, cultural and behavioral silos, the mobilization of extra capacity or resources as well strong leadership during crisis. Moreover, it has been shown that environments in which staff members are encouraged and rewarded for designing mechanisms for solving existing and new problems support economic resilience (Lee *et al.*, 2013; McManus *et al.*, 2008).

Future research may build on the findings presented here along various dimensions. Future research may focus on the role external shocks play in the evolution of regional clusters (Zettinig and Vincze, 2012). In a longitudinal research design, these studies may assess how external shocks relate to the development of regional clusters examining the size and heterogeneity of the composition of regional clusters (Menzel and Fornahl, 2010). These longitudinal case studies may elucidate how the observed changes or persistence in the composition of the regional clusters relate to various outcomes including employment growth or innovation. Finally, economic resilience may be studied at the interface of the network and cluster levels. Recent empirical findings suggest that knowledge flows and network positions differ significantly within clusters (Alberti and Pizzurno, 2015). Future research may therefore shed light on the ways in which varied network positions and knowledge flows within regional clusters relate to economic resilience. For instance, future research may examine whether central network nodes or brokers are more readily able to withstand external shocks. Finally, a further promising avenue for research lies in the investigation of the degree of the persistence of knowledge flows in regional clusters in the face of an external shock.

Note

1. The authors wish to acknowledge the anonymous reviewer #2 for raising this point.

References

Adger, W.N. (2000), "Social and ecological resilience: are they related?", *Progress in Human Geography*, Vol. 24 No. 3, pp. 347-364.

Ahuja, G. (2000), "Collaboration networks, structural holes, and innovation: a longitudinal study", *Administrative Science Quarterly*, Vol. 45 No. 3, pp. 425-455.

Alberti, F.G. and Pizzurno, E. (2015), "Knowledge exchanges in innovation networks: evidences from an Italian aerospace cluster", *Competitiveness Review*, Vol. 25 No. 3.

Baptista, R. and Swann, P. (1998), "Do firms in clusters innovate more?", *International Journal of Industrial Organization*, Vol. 18, pp. 515-535.

Baptista, R. and Swann, P. (1999), "A comparison of clustering dynamics in the US and UK computer industries", *Journal of Evolutionary Economics*, Vol. 9, pp. 373-399.

Baum, J.A.C., Calabrese, T. and Silverman, B.S. (2000), "Don't go it alone': alliance network composition and startups' performance in Canadian biotechnology", *Strategic Management Journal*, Vol. 21, pp. 267-294.

Beaudry, C. and Schiffauerova, A. (2009), "Who's right, Marshall or Jacobs? The localization versus urbanization debate", *Research Policy*, Vol. 38 No. 2, pp. 318-337.

Beaudry, C. and Swann, M.P. (2009), "Firm growth in industrial clusters of the United Kingdom", *Small Business Economics*, Vol. 32 No. 2, pp. 409-424.

Blau, P.M. (1977), *Inequality and Heterogeneity*, Free Press, New York, NY.

Boschma, R.A. (2005), "Proximity and innovation. A critical assessment", *Regional Studies*, Vol. 39 No. 1, pp. 61-74.

Boschma, R.A. and Frenken, K. (2010), "The spatial evolution of innovation networks: a proximity perspective", in Boschma, R.A. and Martin, R. (Eds), *The Handbook of Evolutionary Economic Geography*, Edward Elgar, Cheltenham, pp. 120-135.

Burt, R.S. (1992), *Structural Holes: The Social Structure of Competition*, Harvard University Press, Cambridge, MA.

Capaldo, A. and Petruzzelli, A.M. (2014), "Partner geographic and organizational proximity and the innovative performance of knowledge-creating alliances", *European Management Review*, Vol. 11 No. 1, pp. 63-84.

Cohen, W.M. and Levinthal, D. (1989), "Innovation and learning: the two faces of R&D", *Economic Journal*, Vol. 99 No. 397, pp. 569-596.

Cohen, W.M. and Levinthal, D. (1990), "Absorptive capacity: a new perspective on learning and innovation", *Administrative Science Quarterly*, Vol. 35 No. 1, pp. 128-152.

Cooke, P. (2001), "Regional innovation systems, clusters, and the knowledge economy", *Industrial and Corporate Change*, Vol. 10 No. 4, pp. 945-974.

Delgado, M., Porter, M.E. and Stern, S. (2010), "Clusters, convergence and economic performance", Working Paper No. 10-34, CES, Cambridge, MA.

Dess, G.G. and Beard, D.W. (1984), "Dimensions of organizational task environments", *Administrative Science Quarterly*, Vol. 29, pp. 52-73.

Ernst & Young (2011), *Deutscher Biotechnologie Report 2012*, Ernst & Young, Mannheim.

Ernst & Young (2012), *Deutscher Biotechnologie Report 2012*, Ernst & Young, Mannheim.

Fleming, S. (2001), "Recombinant uncertainty in technological search", *Management Science*, Vol. 47, pp. 117-132.

Gilsing, V. (2005), *The Dynamics of Innovation and Interfirm Networks: Exploration, Exploitation and Co-evolution*, Edward Elgar, Cheltenham.

Glaeser, E.L., Kallal, H.D., Schinkmann, J.A. and Shleifer, A. (1992), "Growth in cities", *Journal of Political Economy*, Vol. 100, pp. 1126-1152.

Gompers, P. and Lerner, J. (2004), "The venture capital revolution", *Journal of Economic Perspectives*, Vol. 15 No. 29, pp. 145-168.

Grabher, G. (1993), "The weakness of strong ties: the lock-in of regional development in the Ruhr area", in Grabher, G. (Ed.), *The Embedded Firm: On the Socioeconomics of Industrial Networks*, Routledge, London, pp. 255-277.

Hill, E.W., Wial, H. and Wolman, H. (2008), "Exploring regional economic resilience", Working Paper 2008-04, University of California, Berkeley.

Holm, J.R. and Ostergaard, C.R. (2013), "Regional employment growth, shocks and regional industrial resilience: a quantitative analysis of the Danish ICT sector", *Regional Studies*, Vol. 49 No. 1.

Hox, J.J. (2010), *Multilevel Analysis. Techniques and Applications*, Routledge, New York, NY.

Jacobs, J. (1969), *The Economy of Cities*, Vintage Books, New York, NY.

Jaffe, A.B., Trajtenberg, M. and Henderson, R. (1993), "Geographic localization of knowledge spillovers as evidenced by patent citations", *The Quarterly Journal of Economics*, Vol. 108 No. 3, pp. 577-598.

Kahl, J. (2014), "The impact of mergers and acquisitions on performance and innovation. empirical evidence from the North American pharmaceutical industry", Dr Kovac, Hamburg.

Koka, B. and Prescott, J.E. (2002), "Strategic alliances as social capital: a multidimensional view", *Strategic Management Journal*, Vol. 23, pp. 795-816.

Lane, P.J. and Lubatkin, M. (1998), "Relative absorptive capacity and interorganizational learning", *Strategic Management Journal*, Vol. 19 No. 5, pp. 461-477.

Lavie, D. and Rosenkopf, L. (2006), "Balancing exploration and exploitation in alliance formation", *Academy of Management Journal*, Vol. 49 No. 4, pp. 797-818.

Lee, A.V., Vargo, J. and Seville, E. (2013), "Developing a tool to measure and compare organizations' resilience", *Natural Hazards Review*, Vol. 14 No. 1, pp. 29-41.

Levitt, B. and March, J. (1988), "Organizational learning", *Annual Review of Sociology*, Vol. 14, pp. 319-340.

Luke, D. (2004), *Multilevel Modeling*, Sage, Thousand Oaks, CA.

McManus, S., Seville, E., Vargo, J. and Brundson, D. (2008), "A facilitated process for improving organizational resilience", *Natural Hazards Review*, Vol. 9 No. 2, pp. 81-90.

March, J. (1991), "Exploration and exploitation in organizational learning", *Organization Science*, Vol. 2, pp. 71-87.

Martin, R. (2012), "Regional economic resilience, hysteresis and recessionary shocks", *Journal of Economic Geography*, Vol. 12 No. 1, pp. 1-32.

Martin, R. and Sunley, P. (2011), "Conceptualizing cluster evolution: beyond the life cycle model?", *Regional Studies*, Vol. 45 No. 10, pp. 1299-1319.

Marzucchi, A., Antonioli, D. and Montresor, S. (2013), "Industry-research cooperation within and across regional boundaries. What does innovation policy add?", *Papers in Regional Science*, forthcoming.

Menzel, M. and Fornahl, D. (2010), "Cluster life cycles: dimensions and rationales of cluster evolution", *Industrial and Corporate Change*, Vol. 19 No. 1, pp. 205-238.

Neffke, F., Henning, S.M. Boschma, R.A. Lundequist, K.J. and Olander, L.O. (2011), "The dynamics of agglomeration externalities along the life cycle of industries", *Regional Studies*, Vol. 45 No. 1, pp. 49-65.

Nelson, R.R. and Winter, S.G. (1982), *An Evolutionary Theory of Economic Change*, Harvard University Press, Cambridge, MA.

Noteboom, B. (2000), *Learning and Innovation in Organizations and Economies*, Oxford University Press, Oxford.

OECD (2012), *Science, Technology and Industry Outlook 2012*, OECD, Paris.

Pendall, R., Foster, K.A. and Cowell, M. (2010), "Resilience and regions: building understanding of the metaphor", *Cambridge Journal of Regions: Economy and Society*, Vol. 3 No. 1, pp. 71-84.

Pfeffer, J. and Salancik, G. (1978), *The External Control of Organizations*, The Maple Press Company, New York, NY.

Porter, M.E. (1990), *The Competitive Advantage of Nations*, The Free Press, New York, NY.

Porter, M.E. (1998), *On Competition*, Harvard Business School Press, Boston, MA.

Pouder, R. and St. John, C.H. (1996), "Hot spots and blind spots: geographical clusters of firms and innovation", *Academy of Management Review*, Vol. 21 No. 4, pp. 1192-1225.

Powell, W.W., Koput, K.W., White, D.R. and Owen-Smith, J. (2005), "Network dynamics and field evolution. The growth of interorganizational collaboration in the life sciences", *American Journal of Sociology*, Vol. 110, pp. 1132-1205.

Raudenbush, S.W. and Bryk, A. (2002), *Hierarchical Linear Models: Applications and Data Analyses Methods*, Sage Publications, Newbury Park, CA.

Raudenbush, S.W., Bryk, A., Cheong, Y.F., Congdon, R. and du Toit, M. (2011), *HLM 7: Hierarchical Linear and Nonlinear Modelling*, SSI Scientific Software International, Lincolnwood, IL.

Rodan, S. and Galunic, C. (2004), "More than network structure: how knowledge heterogeneity influences managerial performance and innovation", *Strategic Management Journal*, Vol. 25 No. 6, pp. 541-562.

Rothaermel, F.T. and Deeds, D.L. (2004), "Exploration and exploitation alliances in biotechnology: a new system of product development", *Strategic Management Journal*, Vol. 25 No. 3, pp. 201-221.

Sampson, R.C. (2007), "R&D alliances and firm performance: the impact of technological diversity and alliance organization on innovation", *Academy of Management Journal*, Vol. 50 No. 2, pp. 364-386.

Simmie, J. and Martin, R. (2010), "The economic resilience of regions: towards an evolutionary approach", *Cambridge Journal of Regions, Economy and Society*, Vol. 3 No. 1, pp. 27-43.

Simonin, B.L. (1999), "Ambiguity and the process of knowledge transfer in strategic alliances", *Strategic Management Journal*, Vol. 27 No. 7, pp. 595-623.

Snijders, T. and Bosker, R. (2004), *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*, Sage, London.

Swann, G.P., Prevezer, J.J. and Stout, D. (1998), *The Dynamics of Industrial Clustering: International Comparisons in Computing and Biotechnology*, Oxford University Press, Oxford.

Tushman, M.L. and Anderson, P. (1986), "Technological discontinuities and organizational environments", *Administrative Science Quarterly*, Vol. 31 No. 3, pp. 439-465.

Tushman, M.L. and O'Reily, A.C. (2004), "The ambidextrous organization", *Harvard Business Review*, Vol. 82 No. 4, pp. 74-81.

Wasserman, S. and Faust, K. (1994), *Social Network Analysis: Methods and Applications*, Cambridge University Press, Cambridge.

Wrobel, M. (2013), "'One for all and all for one': cluster, employment, and the global economic crisis. Evidence from the German mechanical engineering industry", *Papers in Regional Science*, Vol. 94 No. 2, pp. 273-294.

Zettinig, P. and Vincze, Z. (2012), "How cluster evolve", *Competitiveness Review*, Vol. 2 No. 2, pp. 110-132.

Further reading

Ernst & Young (2004), *Deutscher Biotechnologie Report 2004*, Ernst & Young, Mannheim.

Ernst & Young (2008), *Deutscher Biotechnologie Report 2008*, Ernst & Young, Mannheim.

Martin, R. and Sunley, P. (2006), "Path dependence and regional economic evolution", *Journal of Economic Geography*, Vol. 6 No. 4, pp. 395-437.

Park, E. and Ostergaard, C.R. (2012), "Cluster decline and resilience – the case of the wireless communication cluster in North Jutland", paper presented at the DRUID 2012, Barcelona, 4 January, available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2196445

Prevezer, M. (1997), "The dynamics of industrial clustering in biotechnology", *Small Business Economics*, Vol. 9 No. 3, pp. 255-271.

Van der Panne, G. (2004), "Agglomeration externalities: Marshall versus Jacobs", *Journal of Evolutionary Economics, SSI Scientific Software International*, Vol. 14 No. 5, pp. 593-604.

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