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Increasing the national innovative capacity: Identifying the pathways to success using a comparative method

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ABSTRACT

As national innovative capacity is one of the main drivers for long-term economic growth, several countries have tried to increase their capacity by applying a high-tech strategy and supporting this strategy with policies. A better knowledge of successful strategies could support these processes. Previous studies have identified various determinants for a high capacity, but have failed to analyze their interconnections and therefore to derive comprehensive strategies. Applying fuzzy-set qualitative comparative analysis to 17 European countries, we identified different paths leading to a high innovative capacity by combining various determinants. The paths were translated into innovation strategies. Rather than a single strategy, different strategies with the same outcome exist, thus allowing countries to choose the appropriate strategies on the basis of their preconditions. Applying the identified strategies to countries with a low innovative capacity, we found that the UK is strong in all areas except high-tech specialization. Ireland lacks a high share on education spending and venture capital, as do Italy and Spain, which also lack private R&D funding and a high base of journal publications. The Czech Republic, Hungary, Romania, Poland, and Portugal have only a few preconditions for raising their innovative capacity.

1. Introduction

1.1. Research motivation

National innovative capacity (NIC) describes "the ability of a country to produce and commercialize a flow of innovative technology over the long term" (Furman et al., 2002). Consequently, the notion of NIC goes beyond "the realized level of innovative output per se" and claims to reflect "more fundamental determinants of the innovation process" (Furman et al., 2002). In more practical terms, NIC might answer the question of why innovation capabilities on a national level differ from country to country.

In fact, natural imbalances of NIC also apply to the member states of the European Union (European Commission, 2013; Faber and Hesen, 2004). Empirical data on patent volume, a widely accepted proxy for measuring innovative performances (Archibugi and Coco, 2005), show a growing imbalance in countries' innovative outcome, with its "innovation leaders," "innovation followers," "moderate innovators," and "modest innovators" as protagonists in this race (Wohlmuth, 2013). Countries like Germany, Sweden, Denmark, and Finland consistently manage to retain and expand their leadership position in this competition, whereas the remaining countries fail to catch up (European Commission, 2013). Researching EU member states' individual approaches to facilitating innovation – in other words, their national innovation strategies – might provide an answer to the why and also attempt to explain the how, the "hierarchy" within this four-pronged taxonomy.

Much research has already been done on this case (Krammer, 2009) and in summary, no one-fits-all-strategy has emerged. Instead, a certain path dependency among the strategies is observable (Varblane, 2012). The identification of the key success paths leading to high innovation capacity, thus helping stragglers to catch up (Varblane et al., 2007), might be generally useful for both academia and practice. We present a relatively new approach and new results appropriate for many purposes of economic governance, derived from proven concepts, enhanced by fuzzy-set qualitative comparative analysis (fsQCA) as a new but suitable method for innovation research, and grounded on a robust European data set.

1.2. The emergence of NIC research

The roots of this field of study lie in the 1950s, in research contributing to the so-called growth theory. Seminal work paved the way for the contemporary discourse on nations' long-run growth and competitive advantages (Freeman, 1989, 2002; Porter, 1998; Romer, 1986, 1990; Solow, 1956, 1994). These studies pointed out that science, technology, and innovation are the building blocks of economic growth and thereby laid the foundation for three interconnected streams of research and

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literature. As the innovation branch of this taxonomy has evolved toward a consolidated field of research known as the theory of national innovation systems (NIS), some works are positioned in between, bridging modern NIS research, growth theory, and the so-called Schumpeterian school of thought with regard to innovation research (Fagerberg and Srholec, 2008; Fagerberg et al., 2007; Hozumi, 2000; Jungmittag, 2011; Lee and Kim, 2009; Zalewski and Skawińska, 2009).

The term NIS became academically perceptible in the early 1990s. Most of the surveying literature deals with questions of positioning, purpose, and trends (Balzat and Hanusch, 2004; Edquist, 2001; Fagerberg and Sapprasert, 2011; Lundvall, 2007; Niosi et al., 1993; Patel and Pavitt, 1994; Porter and Stern, 2001; Sharif, 2006), and more recent work contributes bibliometric retrospectives on NIS studies (Sun and Grimes, 2016; Teixeira, 2014). Closely linked to these studies and other comprehensive materials (Ács, 2000; Hall, 2010; Lundvall, 2010; Seliger, 2014), another rather small body of literature offers a rigorous attempt at systemic interpretation, aiming for the translation of NIS "from a conceptual framework to theory that feeds a concrete practice" (Edquist, 2009), presenting some sort of innovational ecosystem as a result (OECD, 1997; Oh et al., 2016).

In summary, an NIS can be regarded as a historically grown set of components of the national ecosystem that encourages and supports a country's innovational output. An EU member state's NIS is embedded in an overarching and continuously emerging European innovation system with links to both global and regional innovation systems. Below the national level, sectoral, sub-regional, and local innovation systems have to be distinguished. The NIS is an analytical framework that serves as both model and tool, emphasizing the importance of the system's openness and linkage of different layers as well as coherence and dynamics (Staroske et al., 2000; Sun and Liu, 2010; Wohlmuth, 2013). NISs can be considered as networks with certain characteristics and functions (Wohlmuth, 2013):

- NISs determine the yield, quality, and kind of an economy's innovational activities (Arundel et al., 2007; Ebersberger et al., 2011; Tsai et al., 2009; van de Vrande et al., 2010; Wang et al., 2012; Wonglimpiyarat, 2013; Yoon et al., 2015)
- NISs guide the direction and define the intensity of (cross-border) knowledge flows, technology transfer, commercialization of knowledge, and economic incentives (Etzkowitz and Leydesdorff, 2000; Gomez et al., 2014; Lundvall, 1998; Mowery and Oxley, 1995; Niu, 2014; Paik et al., 2009)
- NISs uncover the linkage between institutions and economic entities and secure a balance between them (Bartels et al., 2012; Djeflat, 2009; Ivanova and Leydesdorff, 2014; Lai et al., 2014; Lee and Park, 2006; Varsakelis, 2006)
- NISs point out starting points for state intervention and policy optimization (Furman and Hayes, 2004; Samara et al., 2012; Schmoch et al., 2006; Solleiro and Castañón, 2005)
- NISs absorb structural and technological change (Antonelli, 2008; Castellacci and Natera, 2013; Hekkert et al., 2007; Schmoch et al., 2006)
- NISs unfold their effects across levels (global, national, regional, subregional, local) (Asheim and Coenen, 2006; Hsu et al., 2014; Jiao et al., 2016; Kenney, 2011; Kwakkel et al., 2014; Nill and Kemp, 2009; Niosi and Bellon, 1994; Spielkamp, 1997; Sun and Liu, 2010; van Lancker et al., 2015)

1.3. Practical use of NIC research: turning innovation strategy into reality

As innovative capacity plays an important role for long-run economic growth (Fagerberg and Srholec, 2008), countries have adopted their innovation strategies accordingly.

For example, Germany, indisputably one of the world's leading economies, possesses and pursues comprehensive strategic agendas dedicated to the technological and scientific development of its economy. The "High-Tech Strategy 2020" of Germany aims for both the retention of its leading position and the securing of global competitiveness and transition into a knowledge-based society on a sustainable basis (Federal Ministry of Education and Research, 2014). The networking of the so-called Triple Helix, consisting of politics, business and science, is at the center of this strategy. In addition, the promotion of SMEs' R&D activities plays a major role (Wohlmuth, 2013).

Importantly, however, the strategy itself should be incorporated into the NIS, particularly in the areas addressed in innovation strategies. Research on the development of NISs shows that continuous monitoring, evaluation, and revision of the NIS are essential to enable intervention by adjusting its cornerstones and interconnections (Edquist, 2009; Wohlmuth, 2013). To this end, new approaches are needed to analyze future trends so as to translate long-term perspectives into institutional arrangements that reflect necessary policy changes and to utilize the NIS for a global competitive strategy (Wohlmuth, 2013). Certain institutional changes and changes in economic incentives as well as the setting of new quantified targets have prerequisites that depend on support from appropriate policies. All levels of government and the parliaments must be fully involved. But how can all relevant policy areas be perfectly matched? How can knowledge demand and supply be optimally organized? Which authorities, companies, and other institutions need to cooperate, and how can they be optimally orchestrated? What weaknesses reside within the linkage of crucial players? (Wohlmuth, 2013).

2. NIC as an analytical framework

2.1. From theory to practice

To provide suitable answers to the above questions, and as a consequence to improve countries' innovation strategies with the help of in-depth knowledge on determinants of innovative capacity, an analytic framework based on NIS research has been developed in parallel to the theoretical principles. Initially, the concept was proposed as an index that could provide regular diagnostics of national performance in invention over time (Romer, 1990; Villa, 1990). The intention was to show the influence of technological change on economic growth. Early research introduced a novel framework called "national innovation capacity" (Furman et al., 2002; Porter and Stern, 2000, 2001, 2004) – a framework that draws on three distinct areas of prior research: ideas-driven endogenous growth theory (Romer, 1990), the cluster-based theory of national industrial competitive advantage (Porter, 1998), and research on NIS that was done in the course of country comparison (Nelson, 1992, 1993). These studies hold that the innovation capacity of countries can be measured by three aspects: the common innovation infrastructure, the cluster-specific environment for innovation, and the quality of their linkage. Since the earlier studies, researchers world-wide have used, enhanced, and adopted the framework for various contexts.

A major field of the framework's application is country development or comparison (Marxt and Brunner, 2013), with a special focus on emerging countries, the so-called catch-up economies (Hu and Mathews, 2005; Liu and White, 2001). In addition, the logics of the NIC framework can be found in various economic studies, such as those that examine the learning and information processes of an economy (Guan and Chen, 2012) or that aim for policy optimization (Herstad et al., 2010; Nill and Kemp, 2009) as well as studies dealing with the efficiency and forecasting of R&D activities (Cullmann et al., 2009; Johansson et al., 2014; Moon and Lee, 2005; Wang and Huang, 2007). Further fields of application are sectoral innovation systems, primarily within the so-called NBIC-cluster (nanotechnology, biotechnology, information and communication technologies, cognitive sciences, and neurosciences) as it gains increasing significance for the global competition of innovative leadership (Chen, 2007; Dodgson et al., 2008; Hu and Phillips, 2011; Kaiser and Prange, 2004; Lo et al., 2013;

Na-Allah and Muchie, 2012; Niosi, 2011; Shapira et al., 2011; Thakur et al., 2012; Wohlmuth, 2013).

2.2. Major differences

Major differences between the scientific and practice-oriented models behind the studies and their underlying data sets lie in the choice of the determinants supposed to influence innovative capacity, the measured value reflecting the innovative capacity, and the statistical method used to examine the interdependencies between them.

As NIC pioneers, Furman et al. (2002) proposed that the common innovation capacity summarizes factors for the economy's aggregated level of technological sophistication, the size of the available pool of scientists, and resource commitments and policy choices that affect innovative capacity. The cluster-specific environment captures the microeconomic environment of nations' industrial clusters. The quality of the linkage measures the interaction between the common innovation infrastructure and industrial clusters, and the relationship between the two is reciprocal. The authors tested their model on panel data for 17 OECD countries, creating a regression model using national patent output from the United States Patent and Trademark Office (USPTO) as the dependent variable. Results showed the significance of gross domestic product (GDP) per capita, patent stock, population, aggregated employed S&T personnel, aggregated research and development (R&D) expenditures, openness to international trade and investment, strength of protection for IP and the share of GDP spent on higher education on the patent output of countries. The stringency of antirust policies had no significant effect. In the construct of cluster-specific environments, findings revealed the relevance of a high percentage of R&D funding by private industry as well as a high degree of specialization. With respect to the quality of the linkage, results showed the relevance of a high percentage of R&D performed by universities. The strength of the venture capital markets had no effect.

Faber and Hesen (2004) built on the Furman et al. (2002) model, testing it with 14 EU countries and adding the sales of product innovations as a further dependent variable. Results showed the positive effect of size of the economy, foreign competition in domestic markets, availability of venture capital, and public R&D intensity on the number of patents. Negative effects were indicated by problems firms encountered during their innovation activities, the presence of a relatively large number of small and medium-sized firms within a country, a high level of economic prosperity, and a relatively large company tax burden.

Lee and Kim (2009) used growth in GDP per capita as a variable and showed the significance of population growth, tertiary education enrollment, average number of patents per million, average of R&D expenditure of GDP, and the average of the ratio of trade to GDP. The study's focus was therefore not on innovation output but on its economic consequences. Results showed that the significance of the variables differs in low-, middle-, and high-income countries.

Filippetti and Peyrache (2011) combined different variables of the dimension business innovation, knowledge and skills, and infrastructure and created their own indicator. Included were number of patents, business R&D, full-time equivalents (FTE) of researchers, scientific and technical articles, public R&D expenditure, size of the labor force with tertiary education, enrollment in tertiary education programs, number of personal computers, number of fixed-line and mobile telephones, number of internet users, gross fixed capital formation, and number of broadband subscribers. Results showed that with respect to technological capabilities, non-Western countries had caught up with Western countries over the previous decade.

Castellacci and Natera (2011, 2013) introduced the concept of the dynamics of national innovation systems. They showed that the dynamics are driven by three innovative capability variables – innovative, scientific, and technological input – as well as three absorptive capacity factors – infrastructures, international trade, and human capital. They used similar but fewer variables than Furman et al. (2002), and added the perspectives of quality of institutions and governance systems as well as social cohesion and economic inequality. However, determinants of national innovative activities have subsequently received only limited attention (Castellacci and Natera, 2013).

In addition to using the number of patents (Ács et al., 2002; Fu and Yang, 2009; Furman et al., 2002; Griliches, 1990; Grupp and Schmoch, 1999; Schmoch, 1999), researchers have employed other proxies for the measurement of innovative capacity. These have included the European Innovation Scoreboard (European Commission, 2013; Schibany and Streicher, 2008), the Global Innovation Index (Dutta et al., 2015; Economist, 2009), the OECD Science, Technology and Industry Scoreboard (OECD Science, Technology and Industry Scoreboard 2015, 2015), and the Innovation Efficacy Index (Mahroum and Al-Saleh, 2013). However, most of these indices merely aggregate single factors and rarely show their interdependencies (Archibugi et al., 2009). The ranking and scores can vary significantly owing to the arbitrary choice of factors, and these models fail to create robust results (Grupp and Mogee, 2004). Therefore, these indices must be treated with considerable prudence when they serve as a basis for scientific research. In addition to these institutionalized composite indicators other barometers and indicator constructs have been applied in NIC research, such as the technology barometer (Loikkanen et al., 2009) or more atypical concepts such as measures of individualism and collectivism and their effects on innovation at the national level (Taylor and Wilson, 2012).

2.3. Critics

While the Furman et al. (2002) model has provided the basis for many other studies, most of these investigations substantially reduced the number of included indicators and thereby lowered the complexity of the model. Faber and Hesen (2004), for instance, did not test indicators shown to be significant by Furman et al. (2002), which might have biased the results. Lee and Kim (2009) used a small number of indicators and took GDP growth as a dependent variable and patent output only as an indicator, thus relegating innovative capacity to being a subpart in their data analysis. Filippetti and Peyrache (2011) used nine variables in creating their index of technological capabilities. However, national innovative capability is a complex phenomenon and requires consideration of a wide set of different indicators in the creation of a comprehensive model.

Panel regression is the method most used in cross-country comparisons of innovation factors (Faber and Hesen, 2004; Fu and Yang, 2009; Furman et al., 2002; Hsu et al., 2014; Varsakelis, 2006; Wang and Huang, 2007). However, this method has several limitations. A regression function presumes the presence of a dependent variable and supposes that this variable can be assessed by a linear combination of different indicators. Unfortunately, whether this function exists in practice is unclear (Woodside, 2013). Possibly some high values for variables are necessary, but a regression function measures only the effects from a mathematical standpoint. Even if such a function exists it may not be linear in nature. In practice, a high value of the dependent variable could be the result of combinatorial conditions. For instance, the amount of venture capital available in a country might only be relevant if a highly educated workforce is available to use it. To resolve this issue, scholars combine variables into indices to apply classical regression analysis. This approach might lead to a good fit of the model but possibly to a poor fit in practice, especially for the comparison of the innovation capacity of countries. A country is a complex system, and assessing all relevant variables is nearly impossible. Therefore, each model is a strong simplification of the ecosystem. Assuming a linear relationship for the model may be a further simplification and inevitably reduces the fit of the model to the real world.

A further limitation of using regression analysis for cross-country studies is the required size of the data set. While discussion of the minimum size of the data set is ongoing, scholars agree that at least 80 data entries are favorable (Martens and Dardenne, 1998). However, in cross-country analyses, comparison of 80 countries or more is often impossible. The quality and availability of data vary greatly, and in-depth data are often available only for developed countries, for example from the statistical databases of the EU or the OECD countries. Researchers overcome this limitation by using panel data to achieve a sufficient number of data entries. However, the scarce availability of historical data strongly limits the number of countries that can be compared. While other studies rely on more general data and compare a large number of countries, they have to include highly, moderately, and underdeveloped countries, which could lead to a bias owing to the different prerequisites of the countries (Lundvall, 2007). The explanatory power of cross-country comparisons may be reduced when the heterogeneity of the innovation systems is not taken into account (Balzat and Hanusch, 2004).

2.4. Means of improvement and contribution to theory

As the discussion of the current models used to examine national innovate capacity reveals, the model by Furman et al. (2002) remains the most appropriate for use with the EU member states, as it is still the most comprehensive NIC framework. However, the original model faces several limitations that have to be overcome beforehand:

- While most of the indicators were quantitatively assessed, the authors relied on qualitative data for strength of IP protection, openness for international trade and investment, venture capital performance, and the stringency of the antitrust policies. A quantitative assessment of these indicators might lead to more robust results.
- The constructs of cluster-specific environment and quality of linkages were each measured by only two variables. Likely important indicators such as the number of newly created businesses were not included – an exclusion that might have led to an undervaluation of the relevance of the construct.
- The model postulates a linear relationship between the patent output and the constructs of innovation infrastructure, cluster-specific environment, quality of linkage, and contributing factors. However, the relationship may not be linear and the model could be an oversimplification. Often, rather than the single conditions themselves the combination of different conditions causes an effect on the outcome (Woodside, 2013). This result might be especially the case when a large set of indicators is used.

These limitations can be removed essentially by two means. The first step is to improve the complexity, choice, and source of the model's indicators, as explained in section three of this article. The second step is to use a comparative approach instead of a regression model to determine the national innovation capacity – an approach that is a novelty in cross-country comparison.

The comparative approach shows the interdependencies between different indicators. Further, it facilitates both the identification of different strategies – that is, combinations of economic prerequisites that lead to a high innovative capacity – and the discussion of advantages and disadvantages for catch-up EU member states. Importantly, fsQCA uses Boolean algebra and fuzzy-set theory to derive causal recipes for a specific outcome (Woodside, 2011). Therefore, different solutions can lead to the same outcome – an effect that is overlooked in regression models. The focus of the proposed model is not on the significance of a single indicator but rather on the combinations of condition configurations, as explained in section three of this article.

Another contribution of the proposed model to theory and practice is the underlying data set, which is drawn from the European Union. The comprehensive statistics available for the EU allow the creation of a rich and precise data set, which is an advantage compared to the vast number of NIC studies that largely face the issue of missing data (Castellacci and Natera, 2011). Moreover, the EU is a rich field of study since conditions for the national innovation capacity might have significantly improved owing to the harmonization of national policies. Further, general conditions like the availability of electricity and broadband internet are homogeneous and therefore there is no bias in comparing developed with less-developed countries. Mixing those countries would have required the inclusion of control variables (Lundvall, 2007), but focusing on the EU allows relying on the availability of a common infrastructure that can be transnationally reflected within the model by a reasonable choice of antecedent conditions.

3. Data and methods

3.1. Data and variables

3.1.1. Data collection

We collected data from 2007 to 2011 for 17 member states of the EU. We drew on several sources in constructing data for 19 variables, including Eurostat as a primary source, the World Bank as a secondary source, and three aggregated indicators supplementing multidimensional data. Eurostat is an institution of the EU that collects, processes, and provides comprehensive data for each member state. Since Eurostat meets all statistical requirements (data consistency, availability, and reliability) for this research, we have used its data for the vast number of our variables, resulting in the need to switch sources in only four cases. Ultimately, the use of World Bank data was necessary in two circumstances. To apply a high degree of stringency, we have also compared the entire set of variables offered at the World Bank database to data from Eurostat. The World Bank offers free and open access to data about development in countries around the globe.

As two variables depict more complex and multilayered facts, we have included data from so-called aggregators. These merge details from various dimensions and observation angles by applying a suitable scoring pattern to one variable. In that respect, the International Property Rights Index provided by the Property Rights Alliance, Washington, D.C., conveys the data for strength of protection for IP to our model (IPRI). IPRI ties up 15 unique sub-variables from the dimensions of legal and political environment, physical property rights, intellectual property rights, and gender equality.

Data aggregation is also necessary with respect to the number of scientific publications, since a trusted list of journals has to be taken as the underlying counting parameter. Therefore, the data are sourced from the information-controlling-decision (ICD) database of the Science Citation Index. This index uses a Thomson Reuters Master Journal List of 3.746 in-scope journals. This open database is cited in many scientific publications, such as the German Federal Report on Research and Innovation, and therefore enjoys sufficient legitimacy and credibility.

Overall, the consideration of many different countries in our research requires some compromise in terms of data sufficiency. Even though all in-scope countries are EU member states and thereby have to meet certain standards, their reporting cycles may differ, leading to missing data within our primary database. Our sample contains a few blank spots, where we had to interpolate missing values for individual variables.[1] As the EU has grown incrementally grown to its current size, the degree of integration, as reflected by member states' enforcement as well as roll-out of equal rules and procedures, differs between countries. Of course, this difference heavily affects Eurostat data availability for certain countries. As we consider data consistency to be more important than all other parameters, we decided to exclude the following EU member states because of insufficient data as of November 2015: Bulgaria, Estonia, Greece, Croatia, Cyprus, Latvia, Lithuania, Luxembourg, Malta, Slovenia, and Slovakia. The following member states are included: Belgium, Denmark, Germany, Ireland, Spain,

[1] Detailed information and spreadsheets can be requested from the authors.

France, the Czech Republic, Italy, Hungary, Netherlands, Austria, Poland, Portugal, Finland, Sweden, the United Kingdom, and Romania.

An overview of the data and sources of all our variables can be found in Table 5 (description of variables) and Table 6 (descriptive statistic) in the Appendix 2.

3.1.2. Output variables

Measuring the output of innovation is difficult. Many studies have used the number of patents as a proxy (e.g., Furman et al., 2002; Faber and Hesen, 2004; Krammer, 2009; Mellahi and Wilkinson, 2010). However, this approach has several limitations. On the one hand, not every innovation is patentable, such as in the area of information technology. Therefore, these innovations are not captured when using the numbers of patents as a dependent variable. On the other hand, not every patent is used to create an innovation. In practice, large corporations often file many patents but are able to use only a certain percentage of them to create products. A comparison of various studies that used different output variables for innovation revealed that the most comprehensively used variable is the share of innovative sales (Hall and Mairesse, 2006). However, this information is available only on the company level and not on the country level. In addition, patents may "provide a fairly reliable measure of innovative activity" (Ács et al., 2002). Therefore, we stick with the number of patents as a proxy for the output of innovation. In addition, we wanted to stay close to the original model (Furman et al., 2002) to ensure comparability. Although that model used the data of the United States Patent and Trademark Office (USPTO), we used the data of the European Patent Office (EPO), since previous work showed no differences in variance explained using the data of the EPO and the USPTO (Faber and Hesen, 2004).

3.1.3. Variables

We retain the initially introduced variables (Furman et al., 2002). However, the choice of our sample countries, the availability of their data, the scientific discourse in this field of research from 2002 to today, and our effort to improve the original model toward our unique model prompt us to make some changes, which we explain in our discussion. A comprehensive overview of our variables in comparison to those of Furman et al. (2002) can be found in Table 5 (in the Appendix 1). In describing our variables, we generally follow the original descriptions provided by Eurostats (2015).

3.1.3.1. International patents per million inhabitants. EPO data refer to all patent applications by priority year as opposed to patents granted by priority year, as is the case of USPTO data (Eurostats, 2015). As a consequence, the EPO data render obsolete the extension of the recording period to "t + 3" as done in the original model of Furman et al. (2002). In addition, expressing these data relative to the population of a country is necessary to exclude the positive correlation between the total of inhabitants and the total of resulting patents, which would favor the more populous countries.

3.1.3.2. GDP per capita; GDP. Given the harmonization tendencies within the EU, the common way of calculating the GDP of its member states is market price-based (stated in Euro). Accordingly, this financial variable conceptually follows market prices instead of purchasing power parities (PPP). Whereas GDP at market prices is defined as the final result of the production activity of resident producer units, PPP and related economic indicators are constructed primarily for spatial comparison and for comparison between different currency areas (Eurostats, 2015).

3.1.3.3. Stock of international patents. If the maximum lifetime of a patent is 20 years, records from a 20-year period would allow assessment of the influence of patent stock. Given the young age of the EU and also the varying dates of countries' entry, a consistent database is available for only about two decades, enabling us to accumulate all patents within a 10-year period for each observed point in time (2007–2011).

3.1.3.4. Aggregate employed scientific and technological (S&T) personnel and labor force. A minor difference between the two models lies in the way of counting. Our data are based on head count, whereas the former models recorded full-time equivalents. The S&T head count data measure the total number of researchers who are fully or partly employed in R&D (Eurostats, 2015).

3.1.3.5. Aggregate R&D expenditures. The R&D statistics are based on the main concepts and definitions of the OECD (2002), which is an internationally recognized standard methodology for collecting R&D statistics (Eurostats, 2015). Again, the underlying scale is GDP at market prices.

3.1.3.6. Openness to international trade and venture capital (VC) performance. In contrast to Furman et al. (2002), we have included quantitative data for these variables instead of qualitative data stemming from survey response. The meaning and purpose of each observation within the research framework remains unchanged.

3.1.3.7. Strength of protection for IP. Again, we have included quantitative data for this variable instead of qualitative data. With the help of IPRI, the data behind this variable capture all aspects around IP protection in favor of the whole model's accuracy. The higher the IPRI value, the greater the IP protection within a country.

3.1.3.8. Share of government expenditure on higher education. For this aspect, the only difference between the two models is the proxy of the total expenditures. Instead of expressing this value in relation to GDP, our database consists of nominal values.

3.1.3.9. Stringency of antitrust policies. In the EU, a harmonized antitrust policy prevails that is enforced among member states by the Treaty on the Functioning of the European Union, codified in Articles 101 and 102 (EUR-Lex - 12008E101, 2015; EUR-Lex - 12008E102, 2015). Hence, no major differences in antitrust prevention exist between those countries that would justify the consideration of this variable within our model. Furman et al. (2002) also showed that antitrust had no significance in their model.

3.1.3.10. Specialization degree. Patents are classified according to the International Patent Classification (IPC) (Eurostats, 2015). The IPC is based on an international multilateral treaty administered by the World Intellectual Property Organization (WIPO) (Eurostats, 2015).[2] Eurostat provides more profound data for this variable than Furman's source did. As a consequence, the application of an auxiliary methodology such as the Ellison and Glaeser Concentration Index was not necessary in our model, since high-tech specialization is directly measured.

3.1.3.11. New business registered. This additional variable documents entry rates of firms across countries and industries. The idea is to relate entrepreneurship to countries' economic development and growth, thereby capturing the role of new businesses as a critical element in the continued dynamism of an innovative economy and industry performance.

3.1.3.12. Capital. For this aspect, our model and the model of Furman et al. (2002) differ in two respects. First, the proxy of the capital stock varies. Instead of expressing this value in relation to GDP, our database consists of nominal values. Second, Furman et al. (2002) excluded residential capital from their observation. Comparable data that isolate this residential share are not available for the EU. In any case, with regard to influence on the model, the relationship should stay the same.

[2] Further details on the IPC classification can be found on the WIPO web site at http://www.wipo.int/.

Table 1
Hypothetical QCA example.

	GDP	Education share	Patents
Country 1	1	1	1
Country 2	1	0	1
Country 3	0	1	0
Country 4	0	0	0

3.2. Method

3.2.1. Description of the method

To overcome the limitations of regression analyses as described in Section 2.3, we used fsQCA as the research method. fsQCA is based on Boolean algebra and fuzzy-set theory and allows identification of different solutions leading to the same outcome. The focus is not on the significance of one variable but instead on identifying certain patterns within the different cases, which have a certain outcome in common.

To explain fsQCA, we describe the underlying method first. In QCA, which is also called crisp-set QCA, each variable can take only the values 0 or 1. If we want to have the patents per year of a country as an outcome variable in a cross-country comparison, we have to decide for each country whether it has a high or low number of patents and assign a 0 or 1. To do so, we use the calibration methods explained in Section 3.2.2. Each data point is considered as one case and an equation is built. To illustrate, we use an example provided in Table 1. In Table 1, we have four countries and the value for high GDP (1: yes, 0: no), high education share (1: yes, 0: no), and high number of patents (1: yes, 0: no). High patents are the outcome, whereas a high education share and a high GDP are possible conditions. Boolean algebra can be used to describe the equations for high patents and low patents.

On the basis of Table 1, the two following equations could be derived:

$$PATENTS = \text{GDP} * \text{EducationShare} + \text{GDP} * \overline{\text{EducationShare}}$$

$$\overline{PATENTS} = \overline{\text{GDP}} * \text{EducationShare} + \overline{\text{GDP}} * \overline{\text{EducationShare}}$$

To find the path leading to high patents, we have to look at the first equation. We can use Boolean minimization to see that GDP leads to high patents in our example. This is essential to what the algorithm of QCA does. It takes each case as a configuration and creates an equation for the positive and negative outcome. Then, the algorithm transforms these equations in the disjunctive normal form by minimizing the terms. The minimized equations are the results of the fsQCA algorithm.

The specialty of QCA is that multiple Boolean solutions exist for one outcome. Extending the example, high GPD and a good availability of venture capital might be independent solutions. Also, combinations of variables might be a possible solution, such as high GDP and high share of GDP spent on education. Therefore, different solutions leading to the same outcome can be identified.

The QCA approach has the disadvantage that it depends strongly on accurate calibration of the variables. Normally, the mean or the average values are used to transform the values into 0 and 1. This way, a country that has 5% fewer patents than the average is treated the same as a county that has 100% fewer. fsQCA was developed to overcome this issue. It uses fuzzy sets for variables and each variable can now take any value between 0 and 1 and not just either of these values, thereby allowing any scale of values to be used—it just has to be transformed on a scale from 0 to 1. The basic function of the algorithm is the same as in QCA. However, the Boolean calculations are replaced by fuzzy set calculations.

A note on fsQCA

Charles Ragin developed the Qualitative Comparative Analysis (QCA) and first described it in his book "The Comparative Method" (Ragin, 1987). With this method he tried to overcome limitations of multivariate methods in social sciences. Data sizes in cross-country analysis were rather small and it was often not possible to create robust results using current quantitative methods. Further, the variables were the focal point of such methods and not the cases (e.g. the country) themselves. The development of QCA proved to be a new, valuable tool for researchers solving these limitations. QCA is so named because emphasis lies on cases rather than on variables similar to qualitative methods. However, QCA was not always applicable as variables could only take the values 0 or 1. Therefore, researchers had to simplify their data, which could result in information loss. To overcome this obstacle, Ragin created fsQCA in 2000 (Ragin, 2000). With fsQCA, researchers can assign any value between 0 and 1 (e.g. 0.3456) to variables. Using calibration procedures, they can now use different scales to measure their variables and then transform the variables to values between 0 and 1.

To apply QCA or fsQCA, researcher can choose from various software packages. We used the standalone software 'fs/QCA' which was co-developed by Charles Ragins (Ragin and Davey, 2014). Further, packages for statistic software like R and Stata are available. An overview of QCA and fsQCA software can be found on the following website: http://www.compasss.org/software.htm

Table 2
Solution of fsQCA models for each construct in each year.

Model	Solutions for infrastructure (i)	Solution for cluster and linkage (c)	Solution for support (s)
2007	1: GDP PER CAPITA * ED SHARE[a] 2: PATENT STOCK * IP[a]	1: SPECIALIZATION * VC[a] 2: PRIVATE R&D FUNDING * SPECIALIZATION * ~UNIV R&D PERFORMANCE[a] 3: PRIVATE R&D FUNDING * VC[a]	1: JOURNALS[a] 2: CAPITAL[a]
2008	1: GDP PER CAPITA * ED SHARE[a] 2: PATENT STOCK * IP[a]	1: ~UNIV R&D PERFORMANCE * VC[a] 2: SPECIALIZATION * ~UNIV R&D PERFORMANCE * ~NEW BUSINESS[a] 3: PRIVATE R&D FUNDING * ~SPECIALIZATION * UNIV R&D PERFORMANCE * ~NEW BUSINESS[a]	1: JOURNALS * ~CAPITAL[a] 2: GDP * CAPITAL[a]
2009	1: R&D[a] 2: PATENT STOCK * IP[a]	1: VC[a] 2: PRIVATE R&D FUNDING * SPECIALIZATION[a]	1: MARKET SHARE[a] 2: JOURNALS * ~CAPITAL[a]
2010	1: GDP PER CAPITA * ED SHARE[a]	1: PRIVATE R&D FUNDING * ~SPECIALIZATION * UNIV R&D PERFORMANCE[a] 2: PRIVATE R&D FUNDING * VC[a]	1: JOURNALS * ~CAPITAL[a] 2: GDP * CAPITAL[a]
2011	1: GDP PER CAPITA * ED SHARE[a]	1: PRIVATE R&D FUNDING * ~SPECIALIZATION[a] 2: NEW BUSINESS * **VC** * PRIVATE R&D FUNDING[a]	1: JOURNALS * ~CAPITAL[a] 2: ~JOURNALS * CAPITAL[a] 3: GDP * ~LABOR[a]
Overall	1: GDP PER CAPITA * ED SHARE[a]	1: SPECIALIZATION * PRIVATE R&D FUNDING[a]	1: ~CAPITAL * **JOURNALS**[a] 2: MARKET SHARE * **CAPITAL** * LABOR * GDP[a]

[a] Consistency above 0.75.

Table 3
Paths for each individual country for each year.

Year	2007		
Country	Innovation infrastructure (i)	Cluster-specific environment and quality of linkage (c)	Contributing factors (s)
Belgium	1: GDP PER CAPITA * ED SHARE	2: PRIVATE R&D FUNDING * SPECIALIZATION * ~UNIV R&D PERFORMANCE	1: JOURNALS
Denmark	1: GDP PER CAPITA * ED SHARE	X	1: JOURNALS
Germany	1: GDP PER CAPITA * ED SHARE	3: PRIVATE R&D FUNDING * VC	2: CAPITAL
	2: PATENT STOCK * IP		
France	1: GDP PER CAPITA * ED SHARE	1: SPECIALIZATION * VC	2: CAPITAL
		2: PRIVATE R&D FUNDING * SPECIALIZATION * ~UNIV R&D PERFORMANCE	
		3: PRIVATE R&D FUNDING * VC	
Netherlands	1: GDP PER CAPITA * ED SHARE	1: SPECIALIZATION * VC	1: JOURNALS
	2: PATENT STOCK * IP		2: CAPITAL
Austria	1: GDP PER CAPITA * ED SHARE	X	1: JOURNALS
Finland	1: GDP PER CAPITA * ED SHARE	2: PRIVATE R&D FUNDING * SPECIALIZATION * ~UNIV R&D PERFORMANCE	1: JOURNALS
Sweden	1: GDP PER CAPITA * ED SHARE	1: SPECIALIZATION * VC	1: JOURNALS
		2: PRIVATE R&D FUNDING * SPECIALIZATION * ~UNIV R&D PERFORMANCE	
	2: PATENT STOCK * IP	3: PRIVATE R&D FUNDING * VC	

Year	2008		
Country	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Belgium	1: GDP PER CAPITA * ED SHARE	X	1: JOURNALS * ~CAPITAL
Denmark	1: GDP PER CAPITA * ED SHARE	3: PRIVATE R&D FUNDING * ~SPECIALIZATION * UNIV R&D PERFORMANCE * ~NEW BUSINESS	1: JOURNALS * ~CAPITAL
Germany	1: GDP PER CAPITA * ED SHARE	1: ~UNIV R&D PERFORMANCE * VC	2: GDP * CAPITAL
	2: PATENT STOCK * IP		
France	1: GDP PER CAPITA * ED SHARE	1: ~UNIV R&D PERFORMANCE * VC	2: GDP * CAPITAL
Netherlands	1: GDP PER CAPITA * ED SHARE	x	2: GDP * CAPITAL
	2: PATENT STOCK * IP		
Austria	1: GDP PER CAPITA * ED SHARE	X	1: JOURNALS * ~CAPITAL
Finland	1: GDP PER CAPITA * ED SHARE	2: SPECIALIZATION * ~UNIV R&D PERFORMANCE * ~NEW BUSINESS	1: JOURNALS * ~CAPITAL
Sweden	1: GDP PER CAPITA * ED SHARE	1: ~UNIV R&D PERFORMANCE * VC	1: JOURNALS * ~CAPITAL
	2: PATENT STOCK * IP	2: SPECIALIZATION * ~UNIV R&D PERFORMANCE * ~NEW BUSINESS	

Year	2009		
Country	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Belgium	1: R&D	X	1: MARKET SHARE
	2: PATENT STOCK * IP		2: JOURNALS * ~CAPITAL
Denmark	1: R&D	X	2: JOURNALS * ~CAPITAL
Germany	1: R&D	1: VC	1: MARKET SHARE
	2: PATENT STOCK * IP		
France	1: R&D	1: VC	2: JOURNALS * ~CAPITAL
		2: PRIVATE R&D FUNDING * SPECIALIZATION	
Netherlands	2: PATENT STOCK * IP	X	1: MARKET SHARE
Austria	1: R&D	X	1: MARKET SHARE
	2: PATENT STOCK * IP		
Finland	1: R&D	2: PRIVATE R&D FUNDING * SPECIALIZATION	2: JOURNALS * ~CAPITAL
Sweden	1: R&D	2: PRIVATE R&D FUNDING * SPECIALIZATION	2: JOURNALS * ~CAPITAL
	2: PATENT STOCK * IP		

Year	2010		
Country	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Belgium	1: GDP PER CAPITA * ED SHARE	X	1: JOURNALS * ~CAPITAL
Denmark	x	1: PRIVATE R&D FUNDING * ~SPECIALIZATION * UNIV R&D PERFORMANCE	1: JOURNALS * ~CAPITAL
Germany	1: GDP PER CAPITA * ED SHARE	2: PRIVATE R&D FUNDING * VC	2: GDP * CAPITAL
France	1: GDP PER CAPITA * ED SHARE	2: PRIVATE R&D FUNDING * VC	2: GDP * CAPITAL
Netherlands	1: GDP PER CAPITA * ED SHARE	X	2: GDP * CAPITAL
Austria	1: GDP PER CAPITA * ED SHARE	1: PRIVATE R&D FUNDING * ~SPECIALIZATION * UNIV R&D PERFORMANCE	1: JOURNALS * ~CAPITAL
Finland	1: GDP PER CAPITA * ED SHARE	X	1: JOURNALS * ~CAPITAL
Sweden	1: GDP PER CAPITA * ED SHARE	2: PRIVATE R&D FUNDING * VC	1: JOURNALS * ~CAPITAL

Year	2011		
Country	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Belgium	1: GDP PER CAPITA * ED SHARE	1: PRIVATE R&D FUNDING * ~SPECIALIZATION	1: JOURNALS * ~CAPITAL
Denmark	x	1: PRIVATE R&D FUNDING * ~SPECIALIZATION	1: JOURNALS * ~CAPITAL
Germany	1: GDP PER CAPITA * ED SHARE	1: PRIVATE R&D FUNDING * ~SPECIALIZATION	2: ~JOURNALS * CAPITAL
France	1: GDP PER CAPITA * ED SHARE	2: NEW BUSINESS * **VC** * PRIVATE R&D FUNDING	x
Netherlands	1: GDP PER CAPITA * ED SHARE	x	3: GDP * ~LABOR
Austria	1: GDP PER CAPITA * ED SHARE	1: PRIVATE R&D FUNDING * ~SPECIALIZATION	1: JOURNALS * ~CAPITAL
Finland	1: GDP PER CAPITA * ED SHARE	X	1: JOURNALS * ~CAPITAL
Sweden	1: GDP PER CAPITA * ED SHARE	2: NEW BUSINESS * **VC** * PRIVATE R&D FUNDING	1: JOURNALS * ~CAPITAL

Bold indicates a necessary condition.

Table 4
Possible strategies to improve the innovations capacity of countries with a low capacity, based on the status quo. Conditions that are already &&met are marked in italics.

Year	2007		
Construct	Innovation infrastructure (i)	Cluster-specific environment and quality of linkage (c)	Contributing factors (s)
Ireland	1: *GDP* PER CAPITA ∗ ED SHARE 2: PATENT STOCK ∗ *IP*	1: *SPECIALIZATION* ∗ VC 2: PRIVATE R&D FUNDING ∗ *SPECIALIZATION* ∗ ~UNIV R&D PERFORMANCE 3: *PRIVATE R&D FUNDING* ∗ VC	2: *CAPITAL*
Spain	x	1: SPECIALIZATION ∗ *VC* 3: PRIVATE R&D FUNDING ∗ *VC*	X
Czech Republic	1: GDP PER CAPITA ∗ *ED SHARE*	X	X
Italy	1: *GDP* PER CAPITA ∗ ED SHARE 2: *PATENT STOCK* ∗ IP	1: SPECIALIZATION ∗ *VC* 3: PRIVATE R&D FUNDING ∗ *VC*	X
Hungary	x	X	X
Poland	x	X	X
Portugal	x	1: *SPECIALIZATION* ∗ VC 2: PRIVATE R&D FUNDING ∗ *SPECIALIZATION* ∗ ~UNIV R&D PERFORMANCE	x
United Kingdom	1: *GDP* PER CAPITA ∗ ED SHARE 2: *PATENT STOCK* ∗ *IP*	1: SPECIALIZATION ∗ *VC* 2: *PRIVATE R&D FUNDING* ∗ SPECIALIZATION ∗ ~UNIV R&D PERFORMANCE 3: PRIVATE R&D FUNDING ∗ *VC*	1: *JOURNALS* 2: *CAPITAL*
Rumania	x	1: *SPECIALIZATION* ∗ VC 2: PRIVATE R&D FUNDING ∗ *SPECIALIZATION* ∗ ~UNIV R&D PERFORMANCE	X

Year	2008		
Construct	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Ireland	1: *GDP* PER CAPITA ∗ ED SHARE 2: PATENT STOCK ∗ *IP*	2: *SPECIALIZATION* ∗ ~UNIV R&D PERFORMANCE ∗ ~NEW BUSINESS 3: *PRIVATE R&D FUNDING* ∗ *~SPECIALIZATION* ∗ *UNIV R&D PERFORMANCE* ∗ ~NEW BUSINESS	1: *JOURNALS* ∗ ~CAPITAL 2: GDP ∗ *CAPITAL*
Spain	x	3: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE* ∗ ~NEW BUSINESS	2: *GDP* ∗ CAPITAL
Czech Republic	1: GDP PER CAPITA ∗ *ED SHARE*	X	X
Italy	1: *GDP* PER CAPITA ∗ ED SHARE 2: *PATENT STOCK* ∗ IP	1: ~UNIV R&D PERFORMANCE ∗ *VC* 3: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE* ∗ ~NEW BUSINESS	2: *GDP* ∗ CAPITAL
Hungary	x	2: *SPECIALIZATION* ∗ ~UNIV R&D PERFORMANCE ∗ ~NEW BUSINESS 3: PRIVATE R&D FUNDING ∗ *~SPECIALIZATION* ∗ UNIV R&D PERFORMANCE ∗ ~NEW BUSINESS	x
Poland	x	3: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE* ∗ ~NEW BUSINESS	X
Portugal	x	2: *SPECIALIZATION* ∗ ~UNIV R&D PERFORMANCE ∗ ~NEW BUSINESS 3: PRIVATE R&D FUNDING ∗ *~SPECIALIZATION* ∗ *UNIV R&D PERFORMANCE* ∗ ~NEW BUSINESS	X
United Kingdom	1: *GDP* PER CAPITA ∗ ED SHARE 2: *PATENT STOCK* ∗ *IP*	1: ~UNIV R&D PERFORMANCE ∗ *VC* 3: *PRIVATE R&D FUNDING* ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE* ∗ ~NEW BUSINESS	1: *JOURNALS* ∗ ~CAPITAL 2: *GDP* ∗ *CAPITAL*
Rumania	x	2: *SPECIALIZATION* ∗ ~UNIV R&D PERFORMANCE ∗ ~NEW BUSINESS 3: PRIVATE R&D FUNDING ∗ *~SPECIALIZATION* ∗ *UNIV R&D PERFORMANCE* ∗ ~NEW BUSINESS	X

Year	2009		
Construct	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Ireland	2: PATENT STOCK ∗ *IP*	2: *PRIVATE R&D FUNDING* ∗ SPECIALIZATION	2: *JOURNALS* ∗ ~CAPITAL
Spain	x	X	X
Czech Republic	x	X	X
Italy	2: *PATENT STOCK* ∗ IP	X	X
Hungary	x	X	X
Poland	x	X	X
Portugal	x	X	X
United Kingdom	2: *PATENT STOCK* ∗ *IP*	2: *PRIVATE R&D FUNDING* ∗ SPECIALIZATION	1: *MARKET SHARE* 2: *JOURNALS* ∗ ~CAPITAL
Rumania	x	2: PRIVATE R&D FUNDING ∗ *SPECIALIZATION*	X

Year	2010		
Construct	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Ireland	1: *GDP* PER CAPITA ∗ ED SHARE	1: *PRIVATE R&D FUNDING* ∗ *~SPECIALIZATION* ∗ *UNIV R&D PERFORMANCE* 2: *PRIVATE R&D FUNDING* ∗ VC	1: *JOURNALS* ∗ ~CAPITAL 2: GDP ∗ *CAPITAL*
Spain	x	1: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE* 2: PRIVATE R&D FUNDING ∗ *VC*	2: *GDP* ∗ CAPITAL
Czech Republic	1: GDP PER CAPITA ∗ *ED SHARE*	X	X
Italy	x	1: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE*	2: *GDP* ∗ CAPITAL
Hungary	x	1: *PRIVATE R&D FUNDING* ∗ *~SPECIALIZATION* ∗ UNIV R&D PERFORMANCE 2: *PRIVATE R&D FUNDING* ∗ VC	X
Poland	x	1: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE*	X
Portugal	x	1: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE*	X
United Kingdom	1: *GDP* PER CAPITA ∗ *ED SHARE*	1: *PRIVATE R&D FUNDING* ∗ ~SPECIALIZATION ∗ *UNIV R&D PERFORMANCE* 2: *PRIVATE R&D FUNDING* ∗ *VC*	1: *JOURNALS* ∗ ~CAPITAL 2: *GDP* ∗ *CAPITAL*
Rumania	x	X	X

Year	2011		
Construct	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Ireland	1: *GDP* PER CAPITA ∗ ED SHARE	1: *PRIVATE R&D FUNDING* ∗ *~SPECIALIZATION* 2: NEW BUSINESS ∗ VC ∗ *PRIVATE R&D FUNDING*	1: *JOURNALS* ∗ ~CAPITAL ‘ 2: ~JOURNALS ∗ *CAPITAL* ‘
Spain	x	2: *NEW BUSINESS* ∗ VC ∗ ∗ PRIVATE R&D FUNDING ‘	3: *GDP* ∗ ~LABOR ‘

(continued on next page)

Table 4 (*continued*)

Year	2011		
Construct	Innovation infrastructure	Cluster-specific environment and quality of linkage	Contributing factors
Czech Republic	1: GDP PER CAPITA ∗ ED SHARE	X	X
Italy	1: GDP PER CAPITA ∗ ED SHARE	2: NEW BUSINESS ∗ VC ∗ PRIVATE R&D FUNDING ‘	3: GDP ∗ ~LABOR ‘
Hungary	x	1: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION 2: NEW BUSINESS ∗ VC ∗ PRIVATE R&D FUNDING	X
Poland	x	X	X
Portugal	x	X	X
United Kingdom	1: GDP PER CAPITA ∗ ED SHARE	1: PRIVATE R&D FUNDING ∗ ~SPECIALIZATION 2: NEW BUSINESS ∗ VC ∗ PRIVATE R&D FUNDING	1: JOURNALS ∗ ~CAPITAL ‘ 2: ~JOURNALS ∗ CAPITAL ‘ 3: GDP ∗ ~LABOR ‘
Rumania	x	2: NEW BUSINESS ∗ VC ∗ PRIVATE R&D FUNDING	X

Consistency above 0.75.

3.2.2. Calibration

As indicated above, the running of a fsQCA analysis requires that the variables be calibrated. A break-point has to be set to assign each configuration a value for a membership in a certain set (Aguilera-Caracuel et al., 2014). For example, during the measurement of the availability of venture capital in countries, the corresponding variable will state whether a specific nation is one of the countries with high venture capital. The idea underlying the calibration is that if a certain threshold value is crossed, an increase in the variable might not result in significant differences in the outcome. For example, the size of the national venture capital market might vary widely depending on whether €100 million or €1 billion are available. While the values in membership and non-membership of countries with a high availability of venture capital can be distinguished, the difference between €5 billion and €7 billion might not influence the outcome even though the absolute difference is larger than in the first case. Both cases would be assigned to membership. Therefore, the calibration of the variables by determining the threshold is one of the key activities in conducting a fsQCA analysis.

Calibration of the variables requires that three points be set: the threshold for full membership, the threshold for full non-membership, and the cross-over point (Ragin, 2014). The cross-over point is the value with full ambiguity as to whether the value is in one or another group. The three calibrations points for our variables are provided in Table 7 in the Appendix 3.

After the threshold values are set, the variables have to be transformed on a scale from 0 to 1 to allow calculation of the fsQCA algorithm. As we rely on quantitative data, we used the direct method of calibration. With the direct method the transformation is directly calculated using a mathematical formula. In contrast, in the indirect method researchers assign values on a six-point Likert scale (1.0, 0.8, 0.6, 0.4, 0.2, 0.0), which is prone to errors. The indirect method is recommended only for working with qualitative data.

Using the direct method, the value for full-membership is set to 0.95, the cross-over to 0.5, and non-membership to 0.05. As the first step for the transformation, a scalar is built based on the natural logarithm of the odds of the membership value. This scalar depends on whether the value to be transformed is greater or smaller than the cross-over point:

$$scalar_{greater} = \frac{\ln(odds\ (0.95))}{|CrossOverValue - UpperThresholdValue|}$$

$$scalar_{lower} = \frac{\ln(odds\ (0.05))}{|CrossOverValue - LowerThresholdValue|}$$

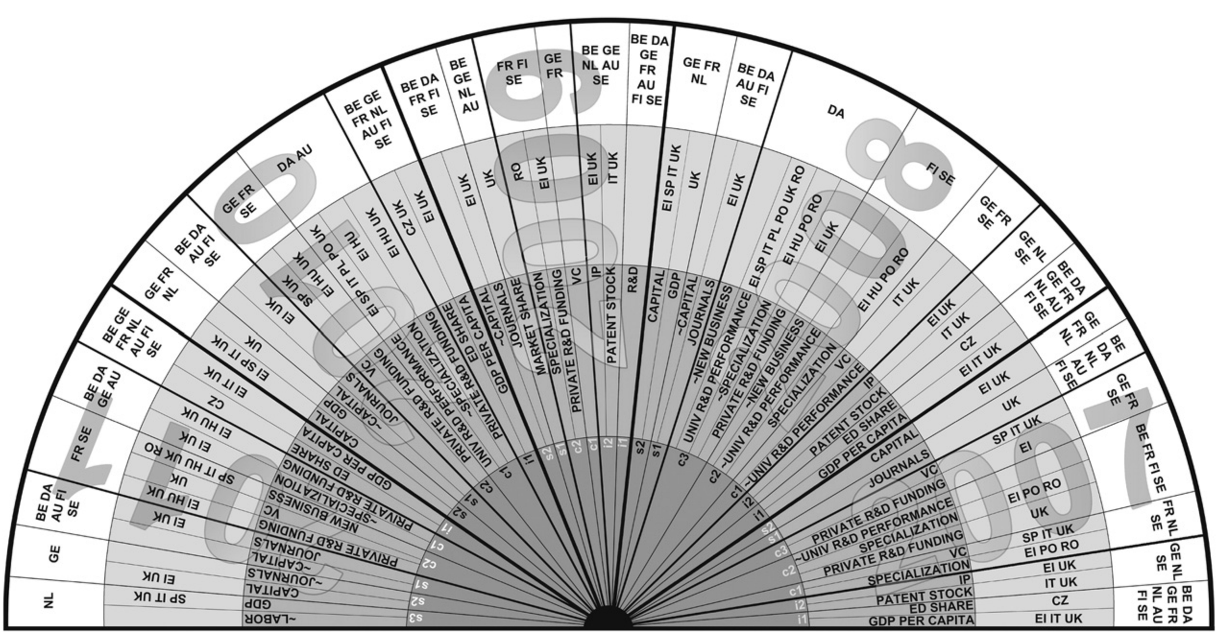

Fig. 1. Individual pathways to innovation leadership. The outer circle shows countries that correspond to entire success pathways, while the second circle reflects countries that partially fulfill a pathway. The third circle depicts each success factor configuration, while the fourth circle displays the innovation constructs, formerly introduced by Furman et al. (2002). All abbreviations correspond to the official list of NATO-country codes.

The next step is to calculate a transformed value by multiplying the difference from the cross-over value of each value of the variable by the respective scalar depending on whether the difference from the cross-over is below or above zero. For above zero the following equation applies:

$$oddsValue = DifferenceFromCrossoverValue * scalar_{greater}$$

For below zero, the following equation will be used.

$$oddsValue = DifferenceFromCrossoverValue * scalar_{lower}$$

The result of the prior calculation is a transformation of the value of the variable into ln odds. Finally, the ln odds are converted into scores that range from 0.0 to 1.0 using the following equation:

$$transformedValue = \frac{e^{oddsValue}}{1 + e^{oddsValue}}$$

The transformed values can be then used to calculate the fsQCA algorithm.

3.2.3. Robustness

Researchers originally developed fsQCA as a small n approach leading to robust results when n equals 15 or above (Ragin, 2008). This characteristic makes fsQCA especially suitable for cross-country comparison, which was also the original field of application (Ragin, 2014). Consequently, fsQCA enables us to perform analyses on the countries of the EU.

Because they are built on logic and not on probabilities, fsQCA models do not have significance criteria like *t*-tests or coefficients of determination. Instead, the models are appraised on the basis of consistency with respect to the proportion of observations that yield the dominant outcome (Muñoz and Dimov, 2015).

The consistency of a model and the underlying solutions should be at least 0.75 (Ragin, 2008) to ensure that its significance is greater than it would be by chance.

4. Results

In the following, we discuss the pathways for high innovative capacity, how they apply to countries with a high innovative capacity, and how they can be used to derive strategies for countries with a low innovative capacity.

Using the patents per million inhabitants as the outcome variable, we created a single model for each year from 2007 to 2011. Thereby, we separately calculated the models for the constructs of the common innovation infrastructure, for the combination of the quality of linkage and the cluster-specific environment, and for the contributing factors. This approach enabled us to study the individual constructs in depth.

We combined the constructs of the quality of linkage and the cluster-specific environment for two reasons. First, a linkage is only possible if a cluster-specific environment exists. Therefore, the availability of the cluster-specific environment has a strong influence. Second, we had only two variables for the cluster-specific environment. Therefore, the solutions from an fsQCA model would have been trivial. To ensure the robustness of our approach, we calculated an overall model including the data from all five years. Further, we checked each country with a membership in our outcome variable to identify which solutions of each construct were included and to analyze the coverage of the solutions, as in prior research (Muñoz and Dimov, 2015). In addition, we compared all solutions with the country with a low capacity, which enabled us to see how far the solutions are from implementing successful strategies. In the following, we discuss the solution for each construct and then the coverage of the cases. An overview of all our solutions can be found in Table 2.

We used the parsimonious solution in nearly all cases. In only two of our models was the consistency of the parsimonious solution below 0.75. In these cases, we used the intermediate solution. Both solutions crossed the consistency threshold. In Table 2, the parsimonious solution is marked in bold in both cases. The solution coverage is above 0.7 for all solutions for infrastructure, above 0.5 for all solutions for cluster and linkage, and above 0.9 for all solutions in the area of support.

4.1. Results for the common innovation infrastructure

Examination of the common innovation infrastructure reveals a combination of high GDP per capita and a high percentage of government expenditures on education as a solution for all years except for 2009. The calculation over all five years confirmed this result. From 2007 to 2009, we see a combination of high patent stock and strength of IP protection as a solution. A high aggregated R&D expenditure is a solution only in 2009.

4.2. Results for the combination of the cluster-specific innovation environment and the quality of linkage

The solutions in this construct vary from year to year. The overall model of all years created the solution of the combination of a high specialization on high-tech patents and a high percentage of private funding. Private funding in combination with other variables is a solution in every year, which shows its strong importance. In addition, the availability of venture capital itself or in combination with other variables can be found as a solution for all five years.

4.3. Results for the contributing and related outcome factors

We found the combination of a high publication rate and low capital stock to be a relevant solution for four of the five years. This solution is also valid for the combined calculation over the whole five years. In addition, we found the capital stock relevant in combination with a high GDP as well as the GDP in various other combinations. The market share of exports in the high-technology field was relevant only in 2009.

4.4. Solution coverage for the countries with a high innovation capacity

To assess the coverage of the solution of the individual constructs, we compared the solutions for the countries with high innovation output. The coverage of the solution of the constructs is high: 57.5% of the cases have a solution for all of the three constructs and all cases have at least two solutions. The cases could be best distinguished through the contributing factors as well as the factors from the common innovation structure. The solutions for the combination of the cluster-specific environment for innovation and the quality of linkage have the lowest effect on explaining the innovative output. The coverage of the solution is summarized in Table 3.

4.5. Solution coverage for the countries with a low innovation capacity

We matched our solutions with the countries with a low innovation capacity. This step is shown in Table 4.

Table 4 shows that the United Kingdom is the country with most paths for a high innovative capacity already in place. The only missing brick is specialization, which is missing for all years. Ireland is in second place, with a high share of education spending and venture capital missing, as with Italy and Spain. Both countries also lack private R&D funding and a high base of journal publications. The Czech Republic, Hungary, and Romania developed first preconditions for future innovation strategies. Poland and Portugal seem to presently have no preconditions to improve their innovative capacity. Fig. 1 condenses the information given in Tables 2, 3 and 4 into one (holistic) chart.

5. Discussion

By using fsQCA, we were able to derive new results regarding national innovative capacity in Europe. We have identified different paths corresponding to innovation strategies leading to a high-patent outcome. With respect to the common innovation structure, we identified the combination of a high GDP per capita and the share of government expenditure on higher education as the most important solution. Having a higher GDP and a high share of government expenditure on higher education potentially leads to a highly educated population. Therefore, one way to increase the innovative output might be to ensure a high education level among a country's population. The second solution we identified is the combination of a high patent stock and the strength of the IP protection. Countries where people can build on previous patents and can ensure that their new patents are well protected tend to have a higher innovative output.

With respect to the cluster-specific environment and the quality of linkage, we see different solutions. The solution identified in most cases is the combination of a high percentage of private R&D funding and a strong specialization in high-tech. This result complies with the current cluster strategy of the EU, which aims for creating central areas focusing on a specific industry or field of technology. In addition, venture capital is a solution in the models for every year, either by itself or in combination with other variables. Therefore, we confirm the findings of Faber and Hesen (2004). An example of using this strategy is the High-Tech Gründerfonds in Germany, a public venture capital fund established by the German government with a current volume of €560.5 million.

Results for the contributing factors reveal that we found two solution paths. The first path is to have a high capital base, as a high capital base is a prerequisite for investments in new high-tech ventures. The second path is to have a large number of international publications, which might be an alternative way to positively influence the patent outcome.

In analyzing the country levels, we were able to derive recommendations for countries with low innovative capacity. The United Kingdom is strong in almost all areas. What is missing is a high specialization in high-tech. A support of this specialization – for example, by implementing a cluster strategy – could lead to an improvement of the innovation capacity.

Ireland also has good bases for improving. A high-tech specialization is already in place, but a high share on education spending is missing. This spending can be influenced by governmental policies. Further, the lack of available venture capital can be reduced by establishing a government fund, as was done in Germany.

Both challenges also apply to Spain and Italy and the same strategies can be used. In addition, private R&D funding is missing. Funding could possibly be increased by offering tax incentives. Further, a high base of journal articles is missing and could be improved by incentivizing universities to publish articles, as is done in the US.

Hungary, the Czech Republic, and Romania have few preconditions to raise their innovative capacity. A solution might be to work together and create clusters in a certain field of technology. If one cluster attains success, another cluster could be established. A similar strategy has been implemented by China.

Portugal and Poland have no preconditions for improving their innovative capacity. Therefore, a strategy could be to partner in projects with countries which have already a high innovative strategy.

6. Implications

Our results emphasize that improving innovative capacity needs a strategic approach. Strategies of countries with high innovative capacity could be identified and applied by other countries. However, the preconditions of different countries have to be taken into account so that the solution with the highest effect can be identified. Rather than focusing on improving single factors, countries should adopt a holistic perspective. Often, a combination of factors –such as a high-tech specialization and private R&D funding to back it up – is necessary to create long-lasting results. We have shown that some countries in the EU already have the preconditions to improve their national innovative capacity. They can implement policies to reach this goal, but other countries are far behind. The lagging countries could initiate partnerships with other countries or apply for support by the government of the European Union. The EU cluster program is a step in this direction.

From a research perspective, our results show the importance of looking at the combination of factors rather than at single factors. Different research approaches such as comparative methods, cluster and factor analyses, or structural equation modeling could lead to further insights into the topics of national innovation systems and national innovative capacity.

7. Limitations and further research

Like all research, our study is subject to some limitations. First, only 17 of the 28 member states of the European Union were included in the study because of a lack of data for the other countries. Looking at countries like Greece or Austria might be very interesting. Eurostat makes a great effort to improve its data base, and further data regarding the excluded countries may become available in the next few years.

Second, a disadvantage of using fsQCA as a research method is that it doesn't produce reliable results when working with panel data sets. Especially when the entries for a specific country are similar for each year, fsQCA will derive a solution with a high consistency from the properties of only one country. To minimize this issue, the number of countries has to substantially outweigh the number of years included in the panel, or the minimum cases for a solution have to be set at least to the number of years included to avoid a solution based on only one country. The second approach was used in this study. We showed that the overall model was similar to the solutions of the single years. This result indicates that fsQCA might also be applicable to panel data. However, this possibility needs intensive study and an empirical comparison of panel regression and fsQCA with multiple data sets.

A further disadvantage in the use of fsQCA is the difficulty of calibration, which is a crucial part of an fsQCA model. The researcher has to assess the threshold value to decide when a value is assigned to one group or another. This assessment is especially difficult for general values like the population. For example, whether a minimum population level is necessary to be able to create patents is unclear. Therefore, we had to rely on average values for assessing the threshold values in all cases. Defining more precise threshold values might increase the robustness of the model. Calibrating fsQCA models needs further discussion.

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Appendix 1

Table 5
Variables and definitions.

Variable	Scale	Full variable name	Definition in our model	Source	Definition in original model
Innovative Output – Outcome Variable					
PATENTS POP $_{j,\,t}$	Number per million inhabitants	International patents per million inhabitants	Patent applications to the European Patent Office by priority year, i.e. the year of the first international filing of a patent, by million persons in the population	Eurostat	Patents granted in United States to the establishment in country j in year (t + 3); for United States, the number of patents issued to US investors associated with an institution such as a company, governmental body and university – divided by million persons in the population
Quality of the common innovation infrastructure (i)					
GDP PER CAPITA $_{j,\,t}$	Euro (€) per capita	GDP per capita	Gross domestic product per capita at market prices	Eurostat	GDP per capita: Gross domestic product in thousands of PPP - adjusted 1985 US$
PATENT STOCK $_{j,\,t(\sum t\,-\,1:t\,-\,10)}$	Number	Stock of international patents	Cumulative patents from: $t_{2007} = 1997–2006$ $t_{2008} = 1998–2007$ $t_{2009} = 1999–2008$ $t_{2010} = 2000–2009$ $t_{2011} = 2001–2010$	Eurostat	Cumulative patents from 1973 until (t − 1)
POP $_{j,\,t}$	Number	Population	Total inhabitants per 1st of January	Eurostat	Population (millions of persons)
FTE S&T $_{j,\,t}$	Number	Aggregate employed S&T personnel	Total researchers, cross-sectors (Business enterprise, Government, Higher Education, Private Non Profit)	Eurostat	Full-time equivalent scientist and engineers in all sectors
R&D € $_{j,\,t}$	Per cent of GDP (at market prices)	Aggregate R&D expenditures	Total amount of R&D expenditures, cross-sectors	Eurostat	R&D expenditures in all sectors in millions of PPP – adjusted 1985 US$
OPENNESS $_{j,\,t}$	Million Euro (€)	Openness to international trade	International trade of EU Member States based on Standard International Trade Classification-product groups; total export volume	Eurostat	Average survey response by executives on a 1–10 scale regarding relative openness of economy to international trade and investment
IP $_{j,\,t}$	Number	Strength of protection for IP	International Property Rights Index	Property Rights Alliance, Washington, D.C.	Average survey response by executives on a 1–10 scale regarding relative strength of IP
ED SHARE $_{j,\,t}$	Percentage	Share of government expenditure on higher education	Expenditure on secondary as percentage of government expenditure on education plus Expenditure on tertiary as percentage of government expenditure on education	Worldbank	Public spending on secondary and tertiary education divided by GDP
Cluster-specific innovation environment (c)					
PRIVATE R&D FUNDING $_{j,\,t}$	Percentage	Private R&D Funding	Expenditure on R&D of business enterprise-sector divided by total expenditure on R&D cross sectors	Eurostat	R&D expenditures funded by industry divided by total R&D expenditures
SPECIALIZATION $_{j,\,t}$	Percentage	Specialization degree	High-tech patent applications to the EPO by priority year divided by total patent applications to the EPO by priority year	Eurostat	Ellison and Glaeser Concentration Index; Relative concentration of innovative output in chemical, electrical and mechanical US Patent Office patent classes
Quality of linkages (c)					
UNIV R&D PERFORMANCE $_{j,\,t}$	Percentage	Percentage of R&D performed by universities	Expenditure on R&D performed by Higher Education sector divided by total R&D expenditures cross sectors	Eurostat	R&D expenditures performed by universities divided by total R&D expenditures
VC $_{j,\,t}$	Million Euro (€)	VC Performance	Venture capital investment, all private equity transactions (cross development phases: acquisition, preparation, founding, post-formation)	Eurostat	Average survey response by executives on a 1–10 scale regarding relative strength of venture capital availability
NEW BUSINESS $_{j,\,t}$	Number	New Business Registered	Number of new limited liability corporations registered in the calendar year	Worldbank	Not included
Contributing and related outcome factors (s)					
JOURNALS $_{j,\,t}$	Number	Publications in academic journals	Number of scientific publications per million inhabitants, using a Thomson Reuters-Master Journal List of 3.746 Journals	ICD database of Science Citation Index	Number of publications in international academic journals, using 1981 journal set
GDP $_{j,\,t}$	Million Euro (€)	Gross Domestic Product	Real GDP at market prices	Eurostat	Gross domestic product in billions of PPP – adjusted 1985 US$
LABOR $_{j,\,t}$	Million People	Labor force, annual average	Number of persons engaged	Eurostat	Number of full-time equivalent persons employed in the labor force
CAPITAL $_{j,\,t}$	Million Euro (€)	Capital	Capital stock based on total financial assets	Eurostat	Non-residential capital stock in billions of PPP – adjusted 1985 US$
MARKET SHARE $_{j,\,t}$	Million Euro (€)	Market share	Share of exports on total (worldwide) trade in high technologies	Eurostat	Share of exports in high-technology industries (among countries in his sample)

Appendix 2

Table 6
Descriptive statistics.

Variable	Min	Max	Med	Average	Std. Dev.
Innovative Output – Outcome Variable					
PATENTS POP $_{j,t}$	1.52	309.49	86.49	122.18	102.21
Quality of the common innovation infrastructure (i)					
GDP PER CAPITA $_{j,t}$	5900.00	44,700.00	30,800.00	27,215.29	11,529.37
PATENT STOCK $_{j,t(\sum t-1:t-10)}$	136.41	231,251.38	13,297.87	31,436.61	53,648.58
POP $_{j,t}$	4,340,118.00	82,314,906.00	10,753,080.00	27,237,488.22	24,999,949.92
FTE S&T $_{j,t}$	19,407.00	522,010.00	63,207.00	130,070.51	135,144.90
R&D € $_{j,t}$	0.45	3.75	1.69	1.86	0.88
OPENNESS $_{j,t}$	29,085.00	1,058,897.00	119,597.00	220,395.05	225,949.86
IP $_{j,t}$	4.70	8.70	7.50	7.27	1.09
ED SHARE $_{j,t}$	0.56	0.74	0.64	0.65	0.05
Cluster-specific innovation environment (c)					
PRIVATE R&D FUNDING $_{j,t}$	0.26	0.74	0.62	0.59	0.12
SPECIALIZATION $_{j,t}$	0.08	0.50	0.20	0.21	0.08
Quality of linkages (c)					
UNIV R&D PERFORMANCE $_{j,t}$	0.16	0.41	0.26	0.26	0.06
VC $_{j,t}$	34.00	34,012.00	512.00	2731.02	5573.61
NEW BUSINESS $_{j,t}$	3274.00	449,700.00	30,934.00	65,008.85	88,637.42
Contributing and related outcome factors (s)					
JOURNALS $_{j,t}$	191.00	2475.00	1128.00	1233.18	567.85
GDP $_{j,t}$	91,415.40	2,609,900.00	311,001.70	696,953.53	747,630.99
LABOR $_{j,t}$	2.17	41.57	5.55	13.01	11.93
CAPITAL $_{j,t}$	188,657.60	19,648,710.00	1,328,129.00	3,298,336.37	4,873,210.74
MARKET SHARE $_{j,t}$	1035.00	142,503.00	15,668.00	28,719.00	33,479.08

Appendix 3

Table 7
Calibration.

Variable	Full membership	Threshold	Full non-membership
Innovative Output – Outcome Variable			
PATENTS POP $_{j,t}$	300	120	0
Quality of the common innovation infrastructure (i)			
GDP PER CAPITA $_{j,t}$	50,000.00	27,000.00	0
PATENT STOCK $_{j,t(\sum t-1:t-10)}$	100,000.00	14,000.00	0
POP $_{j,t}$	80,000,000.00	27,000,000.00	0
FTE S&T $_{j,t}$	500,000.00	130,000.00	0
R&D € $_{j,t}$	4	1.8	0
OPENNESS $_{j,t}$	1,000,000.00	220,000.00	0
IP $_{j,t}$	8	7.2	5
ED SHARE $_{j,t}$	0.75	0.64	0.5
Cluster-specific innovation environment (c)			
PRIVATE R&D FUNDING $_{j,t}$	0.75	0.59	0.25
SPECIALIZATION $_{j,t}$	0.5	0.22	0.1
Quality of linkages (c)			
UNIV R&D PERFORMANCE $_{j,t}$	0.4	0.26	0.15
VC $_{j,t}$	20,000.00	2000.00	0
NEW BUSINESS $_{j,t}$	100,000.00	38,000.00	0
Contributing and related outcome factors (s)			
JOURNALS $_{j,t}$	2500.00	1200.00	0
GDP $_{j,t}$	2000,000.00	585,000.00	100,000
LABOR $_{j,t}$	40	13	0
CAPITAL $_{j,t}$	10,000,000.00	2,300,000.00	0
MARKET SHARE $_{j,t}$	100,000.00	22,500.00	0

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