NATIONAL INNOVATION POLICIES IN THE EU: A FUZZY-SET ANALYSIS

ALEŠ PUSTOVRH[1]
MARKO JAKLIC[2]

Received: 4 December 2013
Accepted: 14 May 2014

ABSTRACT: *This paper argues that innovation policy research can benefit from utilizing new research methods as they might lead to different policy recommendations. It demonstrates this by using a set-theoretic fsQCA method to analyse the data on innovation policies in the European Union (EU). It shows that the use of correlation-based statistical methods is not appropriate for the evaluation of innovation policies due to their causally complex nature that correlational statistical methods cannot unravel. This paper demonstrates this by focusing on the special importance of linkages among actors and innovation commercialisation through entrepreneurship and the notion that they represent a necessary condition for innovation success. Results confirm that the single factor of Linkages & entrepreneurship is the necessary condition for innovation success, thus emphasizing the importance of an open innovation framework for innovation policy-making. Results also show three combinations of sufficient conditions (but no single factor) lead to innovation success. They confirm the causal complexity of innovation policy and confirm that using different research methods will lead to different policy recommendations.*

Keywords: *Open innovation, national innovation systems, QCA, causal complexity, IUS, innovation policy*
JEL Classification: B4, Z1, O3

1. INTRODUCTION

National innovation policies are considered to be one of the most important economic development policies governments have at their disposal. Research on the remarkable economic progress in some countries, sometimes described as economic miracles, cite government innovation policies as a major factor of success – for example, in Taiwan (Kraemer, Gurbaxani, & King, 1992). National innovation policy is considered especially relevant for small, developing economies as a part of their adjustments to the changing international, economic and technological order as well as for improvements to their own economic and technological situations (Lin, Shen, & Chou, 2010).

The foundations of innovation policy-making research lie in scholarly research on innovation. In the past 10 years, innovation research has seen significant changes with the

[1] University of Trieste, Department of Economics, Business, Mathematics and Statistics, Trieste, Italy, e-mail: ales.pustovrh@deams.units.it

[2] University of Ljubljana, Faculty of Economics, Ljubljana, Slovenia, e-mail: marko.jaklic@ef.uni-lj.si

increased focus on new innovation concepts like user-led innovation (von Hippel, 1986, 2005) and open innovation (Chesbrough, 2003). These new concepts have profound effects on innovation policy-making. Their main insight is that the success of innovation policies lies in the recognition of the importance of linkages between actors in innovation systems and of entrepreneurship to commercialise innovation (Herstad, Bloch, Ebersberger, & van de Velde, 2010). Linkages serve as channels for knowledge diffusion and recombination and also facilitate its commercialisation. Entrepreneurship is crucial for commercial success in a world of open innovation (Chesbrough, 2003) as open innovation influences the development of new, open business models (Chesbrough, 2006).

However, new innovation concepts also influence the need to develop new methods for innovation policy research. Innovation policy studies have mainly used traditional statistical research methods for testing their hypotheses. But the use of correlation-based statistical methods is not appropriate for testing due to the causally complex nature of innovation policies. There is strong evidence that methods such as set-theoretic methods could be more suitable (Schneider & Wagemann, 2012, p. 89). We will demonstrate the use of a typical set-theoretic method called fuzzy-set qualitative comparative analysis (fsQCA) for evaluating innovation policy measures, especially the importance of Linkages & entrepreneurship for innovation policy success. More often used in sociology, this method is well suited to the field of policy research (Rihoux & Grimm, 2006).

The intended contribution of the paper is to demonstrate new methods for the analysis of innovation policies that might lead to different policy recommendations. We are doing so by focusing our research on the special importance of linkages among actors and innovation commercialisation through entrepreneurship and the notion that they represent a necessary condition for innovation success. The importance of an open innovation framework for innovation policy-making will thus be emphasised.

2. METHODOLOGICAL AND THEORETICAL BACKGROUND

2. 1. The importance of causal complexity in innovation policy evaluation

In this paper we look at the individual conditions and their interactions for the success of national innovation policies. We focus on several conditions that are needed for their success and test their necessity or sufficiency for successful innovation policy outcomes.

To do so, we first look at the current standard approaches to evaluating the success of innovation policies. There are several approaches for such evaluation, for example systemic (Arnold, 2004), evolutionary (Nill & Kemp, 2009) and participatory (Diez, 2001). There are also some good examples of innovation policies evaluations (e.g. *OECD Reviews of Innovation Policy: Slovenia*, 2012).

During the last few years, an increased number of policy analysts have been opting for multiple case-studies as a research strategy (Rihoux & Grimm, 2006). Their choice is based on the need to gather in-depth insight into the different cases and capture the complexity of the cases while still attempting to produce some level of generalisation (Ragin, 1987). However, the prevailing way of evaluating innovation policies remains over-simplified. The prevailing way of currently evaluating innovation policies is by constructing a single composite index from a set of indicators. These indexes aggregate a large number of indicators reflecting various aspects of science, technology and related factors into a single composite index (Economist, 2009, p. 2). The underlying method for constructing them is based on simple correlation statistical methods such as regression analysis.

Several examples are often used not only in professional discourse but also in scholarly analysis. In Europe, perhaps most widely used is the annual Innovation Union Scoreboard (IUS) (Hollanders, Es-Sadki, & Commission, 2013) and its IUS Summary Index. While initially intended as a benchmarking tool, it has become the central and authoritative source for the European Commission and other EU institutions as well as national policy-making bodies (Adam, 2014). Globally, other indices such as the Global Innovation Index (published by Cornell University, INSEAD and the World Intellectual Property Organization), Bloomberg's Rankings of the most innovative countries or the Economist Intelligence Unit's Ranking of the world's most innovative countries are comprised and publicised.

Methodologically, such approaches are weak. The underlying assumption of such methods is that a higher score on each individual indicator implies better innovation performance. Every improvement of each individual indicator will lead to better innovation performance. This represents a clear example of causal simplicity where researchers focus on linear additive effects of single variables independent of any other causal factors (Schneider & Wagemann, 2012). However, there are good reasons to believe that the phenomenon of successful innovation policy is more complicated than that. Innovations can be explained in a multi-causal manner. (Edquist, 2001, p. 11).

Acknowledging the weaknesses of the prevailing approach, OECD publishes its bi-annual OECD Science, Technology and Innovation Scoreboard (*OECD Science, Technology and Industry Scoreboard 2013*, 2013) as a comparative analysis. It compares member states along a set of indicators but does not try to aggregate them into a single index. Instead, it qualitatively compares innovation trends. While methodologically more sound, this approach does not tackle the issues of the role of individual innovation factors and their influence on innovation success. It also has limited generalisation use. A better method would take into account the complex nature of innovation policy as the interplay of different policy measures and evaluate individual policy measures at the same time. It would incorporate the characteristics of both qualitative and quantitative methods. The focus should lie on causality of innovation policy measures and their necessity or sufficiency for successful innovation outcomes.

We believe innovation policies have the characteristics of causal complexity (Edquist, 2001). There are three characteristics of causal complexity that are defined as:
- equifinality,
- conjunctural causation and
- causal asymmetry.

Empirical analysis and case studies suggest that different and mutually non-exclusive innovation policies can be successful and lead to similar outcomes. For example, the United States has different innovation policies than the Scandinavian countries, and even more different yet are those of South Korea. However, they are all considered successful innovators. They all have high IUS Summary Index scores even though their policy mixes are substantially different. The EU offers some tools to compare innovation policy measures for each country in its Joint Inventory of Policy Measures,[3] which shows the variety of different policy measures national policy-makers implement, even though they often reach very similar innovation success (measured by the IUS Summary Index or by other measurements). In another example, the IUS Summary Index scores for Ireland and the United Kingdom in 2013 are virtually equal at 0.61, even though their corresponding policy mixes are quite different. This is an example of equifinality.

Additionally, there is clear evidence that single policies can unfold only in combination with other precisely specified conditions. An example is a policy measure to support the establishment of a venture capital (VC) industry to help support the commercialisation of technologies. The case study of a very successful government intervention by the Israeli government in 1990s (the Yozma instrument) has been replicated by a number of countries but with much less success – for example Slovenia and Croatia (Švarc, 2006); neither Slovenia nor Croatia experienced such successful development of their respective VC industries as was observed in Israel. The reason for the lack of success probably lies in a lack of other conjunct policy measures – for example, the technology-transfer mechanisms and structure in Israel that were significantly different than those in EU countries. This is an example of conjunctural causation.

Finally, policies that lead to innovation success are not the same as the (lack of) policies leading to innovation failure. It is an over-simplification to claim that a lack of innovation success is the result of lacking innovation policies that were sufficient to lead to innovation success in other countries. If this were sufficient for innovation success, all the countries would copy successful policies, and soon after they would become successful themselves. In reality, implementing exactly the same innovation policies that were successful in Israel will not turn a country like Slovenia into a leading venture capital provider, just as the lack of a developed venture capital industry is not the only culprit of less successful innovation outcomes. Causal conditions leading to the presence of successful innovation outcomes are of only limited use for the causal role of its absence. This is an example of causal asymmetry.

Statistical regression-based methods cannot achieve causally complex results as they cannot unravel set relations and the form of causal complexity that comes with it. For example, correlation is a symmetric measure in the sense that if we are able to explain the positive or high values of a dependant variable, then we are also able to explain the negative or low values of the dependent variable (Schneider & Wagemann, 2012). In contrast, set-theoretic relations such as sufficiency and necessity are indicated by asymmetric set

[3] Available at http://erawatch.jrc.ec.europa.eu/erawatch/opencms/research_and_innovation/

relations. Asymmetry describes the fact that insights into the causal role of a condition are of limited use for the causal role of its absence. The explanation of the occurrence of the outcome does not necessarily help us explain its non-occurrence.

Data patterns of correlation also look quite different from those of a set relation. It is absolutely possible for a researcher to find a perfect set relation but fail to detect any strong correlation between the variables. Correlational methods rely on both the presence of conditions (variables) at the same time as the presence of the outcome and their absence. They have equal analytic relevance. On the contrary, set-theoretic methods look at cases where both conditions and outcomes are absent as irrelevant for explaining the causation. They should be analysed by developing another set-theoretic model with a new, negated outcome. The conditions influencing the presence of an outcome (in this case innovation success) are not the same as the conditions influencing its absence. Set-theoretic models incorporate this asymmetry, while correlation-based models are inherently symmetrical. Methods like ordinary least squares in which the sum of the square roots of distances between dots and regression line are minimised are a direct expression of this symmetry (Schneider & Wagemann, 2012, p. 84).

Methodologically induced assumptions of simplicity run the risk of generating oversimplified representations that are very much detached from the cases and data patterns that underlie the analysis of innovation policies. They do not correspond to the complexity of the social world and lead to wrong policy recommendations and a waste of resources.

2.2. Set-theoretic methods are more suitable for researching causal complexity

As correlational statistical methods cannot achieve causally complex results, they are not suitable for researching causally complex phenomena. Unlike conventional statistical techniques which are based on examinations of sufficiency (Ragin, 2000), set-theoretic methods can examine the links between various combinations of causal conditions and the outcome as both necessary and sufficient conditions. They can systematically and formally examine the necessary and sufficient conditions for the outcome. This is important here, as it is yet to be established whether certain innovation policy measures are either necessary and/or sufficient for countries to achieve desired innovation outputs. The use of set-theoretic methods means that causal relationships between conditions and the outcome can be explored. These findings may, in turn, lead to clearer policy implications than would be the case from an analysis of the marginal effects obtained from regression analyses (Fiss, 2011).

This paper uses a relatively new approach of a set-theoretic method to show that other methodological approaches will yield different results and a different view on the innovation process and consequent innovation policy-making. This approach allowed for a detailed analysis of how causal conditions contribute to the outcome in question. It was based on a configurational understanding of how causes combine to bring about outcomes (Fiss, 2011, 2012). We have used the most often used set-theoretic method, called qualitative comparative analysis (QCA).

The original QCA method was developed 27 years ago (Ragin, 1987) and is based on the binary logic of Boolean algebra. Essentially, QCA examines how the membership of cases in the set of causal conditions is linked to the membership in the outcome set (Allen & Aldred, 2011). Cases are best understood as configurations of attributes. Their comparison allows a researcher to examine instances of the cause and outcome to understand patterns of causation. It uses set–subset relations to examine causal patterns of necessity and sufficiency. A condition is necessary, if, whenever the outcome is present, the condition is also present. Additionally, the condition is sufficient if, whenever the condition is present, the outcome is also present (Schneider & Wagemann, 2012, p. 76). The QCA method uses formal procedures to test the necessity and sufficiency of conditions for the outcome. In this paper, we demonstrate the use of these procedures in innovation policy research and evaluation.[4]

An additional benefit of the QCA method is that it also attempts to maximise the number of comparisons that can be made across the limited number cases under investigation. The technique aims to resolve the problem of a small number of case observations by allowing inferences to be drawn from the maximum number of comparisons that can be made across the case under analysis. As such, it is particularly useful when analysing country comparisons as their numbers are inherently small but at the same time too high for the use of other qualitative methods such as case studies.

The original QCA method was based on crisp values of 1 indicating the presence of a particular set and 0 indicating its absence (Ragin, 2007). Due to its binary logic, this method is today known as a crisp-set QCA (csQCA) and has been criticised as the researcher has to determine the values of each variable. But as most variables are essentially continuous, the division will always be arbitrary. A second, related problem is the fact that the technique does not allow an assessment of the effect of the relative strengths of the independent variables (as they can only have two values). In order to avoid these problems, the QCA method was upgraded with fuzzy-set theory to address partial memberships in the set (Ragin & Rihoux, 2009). This fits well with innovation policy research as individual innovation policy indicators are often normalised and based on a continuous scale. On the other hand, fuzzy-sets are a powerful tool that allows researchers to calibrate partial membership in sets without abandoning the core set-theoretic principles (such as subset relations). They are at the same time qualitative and quantitative as they incorporate both kinds of distinctions in the calibration of the degree of set membership (Ragin & Rihoux, 2009).

Based on this reasoning, we have used a set-theoretic method of fuzzy-set qualitative comparative analysis (fsQCA) to test innovation policy measures. Specifically, we have used fsQCA to analyse the causal complexity of innovation policies, aiming to assess the

[4] For an excellent introduction into QCA methods, its theory and procedures, the reader is referred to Schneider and Wagemann, 2012.

relationship between combinations of 'causal conditions' and the related output (Ragin & Rihoux, 2009). We demonstrate this analysis based on an idea originating from the open innovation paradigm.

2.3. Open innovation and its influence on innovation policy-making

The theoretical background of this paper is the premise that innovation is not a closed system but rather is dependent of the extent of mutual cooperation. Innovation policies need to take this into account and not focus solely on supporting individual companies but on their collaboration as well. This premise is central to the open innovation paradigm (Chesbrough, 2012). It assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as the firms look to advance their technology.

The implications of open innovation systems on innovation policies have been predicted and studied since the definition of the concept. One of the open innovation's main arguments is that linkages between actors serve as channels for knowledge diffusion and recombination. Lack of linkages and networking across organisational boundaries represents a system failure, as do lock-ins to specific collaboration partners, sources of ideas and information or an excessive overall 'closure' of learning processes (Herstad et al., 2010). These failures need to be tackled in a way similar to market failures – through policy intervention (Klein Woolthuis, Lankhuizen, & Gilsing, 2005). Recently, several papers and studies discussed the question of how national innovation polices can be reframed in a context of open innovation (De Backer, Cervantes, Van De Velde, & Martinez, 2008; Ebersberger, Herstad, Iversen, Kirner, & Som, 2011).

The central idea behind open innovation is that, in a world of widely distributed knowledge, companies cannot afford to rely entirely on their own research but should instead buy or license processes or inventions (i.e. patents) from other companies. In addition, internal inventions not being used in a firm's business should be taken outside the company (e.g. through licensing, joint ventures or spin-offs) (H. W. Chesbrough, 2003). In other words, linkages between companies and other institutions are crucial for the successful implementation of innovation in companies. However, innovation itself is only one part of the process – the value creation part. To ensure commercial success, companies also need to capture the newly created value. Claiming ownership of the intellectual property for newly developed technologies and finding different paths to the market are also crucial parts of the open innovation concept (H. W. Chesbrough, 2006). This means that companies of all sizes can create and capture value from ideas and technologies. Open innovation is becoming increasingly relevant to entrepreneurs and the organisations that support them. This second part of the open innovation concept essentially emphasises entrepreneurship and the importance of business ecosystems for established companies and startups (Mcphee & Segers, 2013). Without successful linkages between different innovation actors, there can be no successful innovation and thus no value creation. Without successful entrepreneurs, positioned in a vibrant business ecosystem, there can be no value captured from successful innovation. Both are necessary for a successful national innovation system.

National innovation policies have already started to adjust to the recent changes. Some successful examples include Ireland (Irish Innovation Taskforce, 2010), Taiwan (Lin et al., 2010) and the US (Technology, 2010). On the contrary, innovation policies that do not adjust to open innovation will not be successful (Svarc, 2006). Far from becoming redundant, innovation policies remain an essential element of industrial policy.

Based on the insights contributed by the new innovation concept of open innovation, we will use an example of Linkages & entrepreneurship, as defined in an open innovation framework, and demonstrate that they are a necessary condition for the success of innovation policies.

Hypothesis 1: Linkages & entrepreneurship are a necessary condition for the success of national innovation policies.

The use of a novel research method has allowed us to test not only for the necessity but also for the sufficiency of Linkages & entrepreneurship as well as other conditions for innovation success. We discuss these conditions in more detail below.

3. DATA AND METHODS

Using fsQCA, this research has focused on analysing different innovation policies in the EU. The EU has recognised the importance of specific policies that focus on improving innovation outcomes – the 'narrow' innovation policies – in order to improve its growth prospects in the newly globalised environment. It recognised it cannot compete in this new environment unless it became more innovative (Commission, 2013a). The main current EU innovation policy is the Innovation Union, one of the Europe 2020 growth strategy's flagship initiatives (Commission, 2013c). Its aim is to set out a strategic approach to innovation, seeking to boost research and innovation performance in Europe by getting promising ideas and discoveries to the market faster. A crucial part of this approach is building 'bridges' connecting science, technology and markets (Commission, 2013b).

An integral part of the Innovation Union is the annual IUS assessment. It provides a comparative assessment of the research and innovation performance of the EU27 Member States and the relative strengths and weaknesses of their research and innovation systems. It has become the benchmark for innovation policy evaluation in the EU and helps member states assess areas in which they need to concentrate their efforts in order to boost their innovation performance (Hollanders et al., 2013). The calculation of the annual composite IUS Summary Innovation Index allows the preparations of country rankings and assures considerable publicity in the media and in the interested public (Schibany & Streicher, 2008). This is also likely one of the most important results of the IUS initiative which has assured its continuation into its 14th year.

However, there is also considerable criticism of this approach. New understanding of innovation processes has resulted in changes to the IUS reports and indicator selection. Particularly, the constructs of user innovation and open innovation and the emergence of service innovation have influenced the selection of indicators that comprise the composite index. However, this selection has been limited due to lack of new data as IUS indicators are based on official statistical sources. It also strongly relies on the Community Innovation Survey, a biannual series of harmonised surveys that are executed by the national statistical offices throughout the EU. Lack of sufficient data has certainly influenced the indicator selection, but the overall criticism was more directed at the arbitrary selection of indicators, which is not based on an underlying model of innovation. For example, a methodological review of IUS, implemented by the authors themselves an IUS methodological review themselves (Hollanders & van Cruysen, 2008) lists a number critics, including Rammer (2005) who states that "new indicators should be identified and selected on . . . a conceptual analysis rather than on a simple statistical correlation analysis".

Among other things this has resulted in apparent high-tech bias. Furthermore, the indicators should focus on questions of data quality, including reliability as well as availability for large number of countries. The link between indicators and policies should distinguish between performance indicators and policy indictors. As Schibany (2008) noted, "Any concise inference regarding the selection of indicators and . . . their mutual interaction is mostly ignored". Additional methodological criticism emphasised the drawbacks of the construction of a single composite indicator, missing the complexity of the innovation process (Cherchye, Moesen, & Van Puyenbroeck, 2004). The low quality of data also raises significant issues of multicolinearity between indicators. Multicolinearity between indicators is a typical problem originating from the statistical method used for the construction of the composite IUS Summary. As discussed above, using correlation statistical methods for causally complex phenomena (like innovation policies) is not recommended (Schneider & Wagemann, 2012).

3.1. Operationalisation of the QCA analysis

To perform the fsQCA analysis of the innovation policies, we proceeded along the following steps:

1. We started by compiling a database of existing indicators on innovation policies in the EU.
2. These indicators were than calibrated and converted to (fuzzy) set membership scores.
3. We followed this with the construction of the truth table – a data matrix wherein each row of the table is associated with a special and distinct combination of attributes, and the full table consists of all possible combinations of attributes. We then sorted all empirical cases into the rows of the truth table.
4. We started our analysis with an analysis of necessary conditions and followed that with an analysis of sufficiency.
5. We performed the analysis of sufficiency by using the truth table algorithm: We

minimised the truth table by reducing the number of rows based on the minimum number of cases required for the solution and the minimum consistency level of a solution (consistency meaning the degree to which cases correspond to the set-theoretic relationships expressed in a solution). In fuzzy sets we simply estimated the consistency as the proportion of the cases that are consistent with the outcome.
6. We followed the Standard Analysis procedure to minimise the truth table in order to obtain three solutions – complex, parsimonious and intermediate. Based on the simplifying assumptions, we used an intermediate solution to interpret the results.

To execute the QCA procedure, we used the fs/QCA software (Ragin, Kriss, & Davey, 2006; available at www.fsqca.com).

3.2. Dataset of innovation policy indicators

First, we compiled a database of existing indicators. In order to demonstrate the differences between correlational statistical methods and set-theoretic methods, we used the same data as in the original IUS. By using the same underlying data but obtaining different results, we intended to demonstrate differences between methods. This means that we needed to test the same innovation inputs into innovation activities and the activities themselves (defined as innovation enablers and innovation activities in the IUS) that were tested in the original IUS summary index. The data on human resources, research systems, finance and support, firm investments into research and innovation and Linkages & entrepreneurship were obtained by using the IUS data.

We used the existing dataset of IUS indicators IUS (Commission, 2012). In the IUS, these measures were split into two groups of indicators:
1. Enablers:
    a. Human resources index (summary index comprised of three indicators: new doctoral graduates, population with completed tertiary education and youth with upper secondary level education)
    b. Open, excellent and attractive research systems (three indicators on international scientific co-publications, scientific publications among the top 10% most cited and non-EU doctoral students)
    c. Finance and support (two indicators on public research and development [R&D] expenditure and on VC financing)
2. Firm activities:
    a. Firm investments (two indicators on business R&D expenditure and non-R&D innovation expenditure)
    b. Linkages & entrepreneurship (three indicators on [SMEs] innovating in-house, innovative SMEs collaborating with others and public–private co-publications)
    c. Intellectual Assets (four indicators on Patent Cooperation Treaty [PCT] patent applications, PCT patent applications in societal challenges, community trademarks and community designs)

All indicators used were defined in the same way as in the original IUS. That means they are based on a set of indicators measuring the success of national innovation policies for each particular condition rather than measuring concrete activities on the level of companies.

As our hypothesis was focused specifically on Linkages & entrepreneurship, we could see that the composite indicators are comprised of internal SME innovation, SME innovation linkages and general science and innovation linkages. While more and better indicators on Linkages & entrepreneurship would be desirable, we have used the existing composite index in order to demonstrate the new research method and its benefits in innovation policy research. The IUS is also very useful as it collects a large database of innovation indicators and innovation policy measures that can be used for analysis with methods other than the IUS Summary Index.

While IUS data are available for more than 50 countries, we were primarily interested in identifying differences between the countries of the EU or those closely connected to them (usually in membership talks or in special arrangements with the EU). This assured relatively similar institutional and regulatory backgrounds, and, to a lesser extent, cultural backgrounds. Thus, we could assume that the differences in the innovation output of countries were the result of innovation policies and not differences in framework policies or the different institutional structures of individual countries. In the end, we used the dataset for 23 countries.

We used the average value for the period between 2007 and 2009 for our indicators. We did not use the indicators for measuring economic effects and innovators as the authors of the index classified them as measures of innovation output. Our research design meant that we needed to use a different measure of innovation output – the (aggregate) IUS Summary Index itself.

3.3. Data calibration

In order to operationalise our research, we constructed fuzzy-set scores for each indicator and for the output of each country based on four-item scale. The QCA analysis would normally request its own calibration thresholds for the data; however, in this case, the aim of the paper was the analysis of IUS data. They are already normalised, so it would be against the aim of the paper to devise different measures than the ones originally used in the IUS. For the same reasons, it would be unreasonable to use any other set-theoretic method than fsQCA as individual cases (countries) have already obtained index scores spanning the full range between 0 and 1.

The IUS reporting had delineated countries into four groups. The Summary Innovation Index score of Innovation leaders is 20% or more above that of the EU27; of Innovation followers, it is less than 20% above but more than 10% below that of the EU27; of Moderate innovators, it is less than 10% below but more than 50% below that of the EU27; and for Modest innovators, it is below 50% that of the EU27. These thresholds were used for the direct calibration of the data and their subsequent grouping into one for the four groups that were given the same fuzzy score. For example, the EU's average Summary Innovation Index score for 2010 was 0.53255 – 120% of that was 0,6391, 9% value was 0.4793 and 50% value was 0.2663. These values were used as the three points for the direct method of calibration and the thresholds for the groups that were given the same fuzzy score. All countries with an IUS Summary Index score higher than 0.6391 were given the fuzzy score of one, those between 0.6391 and 0.4793 were given a fuzzy score of 0.66 etc. We decided to use the same calibration for IUS factors (composite indicators, conditions in the QCA analysis) as well.

3.4. Analysis of necessity

We started the data analysis with the analysis of necessary conditions for the presence of the outcome using the formal QCA procedures. The results of this analysis implied that the Linkages & entrepreneurship fulfil the criteria for a necessary condition for the outcome IUS as they had a very high consistency of almost 0.98 (they also had high coverage). This result was confirmed by the XY plot for the variable of Linkages & entrepreneurship as it showed a high probability of necessity of this condition with a single observation (Spain) visible above the bisecting line and all others lying below the line as expected to fulfil the criteria of necessity (whenever the outcome is present, the condition is also present). This confirmed our central hypothesis that this condition is necessary. The formal procedure conducted on the analysis of necessity did not show any other necessary conditions.

3.5. Analysis of sufficiency – The truth table algorithm

We proceeded with the formal analysis of sufficiency. The XY plots also suggested that Finance and support could be a sufficient condition by itself. However, further examination showed that three cases (Estonia, Norway and France) lay below the bisecting line, thus breaking the rule for sufficiency (whenever the condition is present, the outcome is also present). These cases will be noted for further examination when analysing the results.
We proceeded with the truth table algorithm. After hiding the logical reminder rows (in this case, rows with no recorded cases), we coded the outcome with 1 if the raw consistency was above 0,99. This threshold was not only theoretically sound, but it was also marked with a clear break in the consistency values as the next row had a low consistency score of 0,83 and a relatively low PRI consistency score – potentially implying that this sufficiency condition could also be the sufficiency condition of the negated outcome ~Y. The truth table thus obtained is presented in Table 1:

Table 1: *Fuzzy-set truth table*

A	B	C	D	E	F	Number of cases	Y	Raw consistency	PRI consistency
1	1	1	1	1	1	8	1	1	1
1	1	0	1	1	0	1	1	1	1
1	1	1	0	1	1	3	1	1	1
1	1	0	1	1	1	1	1	1	1
1	0	0	1	1	0	1	1	1	1
0	0	1	1	1	0	1	1	0,99	0,97
1	1	1	0	1	0	1	0	0,83	0,75
0	0	0	1	1	0	1	0	0,8	0
0	1	0	0	0	0	1	0	0,75	0
0	0	0	1	0	1	1	0	0,67	0
0	0	0	0	1	0	1	0	0,6	0
0	0	0	0	0	0	1	0	0,43	0
0	0	0	1	0	0	2	0	0,37	0
1	0	0	0	0	0	1	0	0,25	0

Notes: *The consistency threshold of 0,85 was used due to low PRI scores in truth table rows 7 and 8
** Written in Boolean algebra: (A*B*C*D*E*F)+(A*B*~C*D*E*~F)+(A*B*C*~D*E*F)+ (A*B*~C*D*E*F)+(A*~B *~C*D*E*~F)+(~A*~B*C*D*E*F)=Y where
A= hr_c= Human resources
B= rs_c= Open, excellent and attractive research systems
C= fs_c= Finance and support
D= fi_c= Firm investments
E= la_c = Linkages & entrepreneurship
F= ia_c = Intellectual assets
Y (outcome) = IUS = Innovation Union Scoreboard innovation performance score

3.6. Logical minimisation procedure

Three solutions were obtained from the truth table using the Standard Analysis procedure.
Complex solution:
(A*~C*D*E*~F)+(A*B*C*E*F)+(~A*~B*C*D*E*~F)*(A*B*~C*D*E)+(A*B*D*E*F)=Y
Parsimonious solution:
(A*D)+(C*D)+(A*F)+(B*F)+(C*F)+(E*F)=Y
Intermediate solution:
(E*D*C)+(E*D*A)+(F*E*C*B*A)=Y ; E*((D*C)+(D*A)+(F*C*B*A))=Y

We decided to use the intermediate solution as the best one for further analysis as it was based on the most plausible, theory-based assumptions for logical reminders. These assumptions were based on easy counterfactuals and are normal in the Standard Analysis as part of the QCA procedure. Both methods are part of the Standard Analysis procedure and are essentially mathematical tools that enable us to obtain useful solutions from a limited number of cases.

The simplifying assumptions that were used were directional expectations and prime implicants. The directional expectation used presumed that the presence of each individual condition would have a positive effect on the presence of the outcome based on a sound theoretical background. Prime implicants had to be used as a mathematical tool in the logical minimisation procedure due to limited diversity. We have marked four prime implicants (A*F, B*F, C*F and E*F) to obtain the intermediate solution, indicating that different combinations of conditions combined with the condition of F (Intellectual Assets) were used to obtain the solution.

4. RESULTS

Our chosen solution has recognised three paths to a successful IUS Summary Index:

E*((D*C)+(D*A)+(F*C*B*A))=Y or

Linkages & entrepreneurship AND

((Finance and support AND Firm investments) OR (Firm investments AND Human resources) OR (Human resources AND Open, excellent and attractive research systems AND Finance and support AND Intellectual assets))
lead to the presence of the outcome (innovation success, measured as a high IUS Summary Index Score).

Table 2 presents the analysis of sufficient conditions and parameters of fit for the outcome of 'Innovation Union Summary Index success'.

Table 2: *Analysis of sufficient conditions for the outcome of 'Innovation Union Summary Index success'*

Solution	E*D*C	+	E*D*A	+	F*E*C*B*A
Single country coverage	Estonia		Ireland, Austria, Slovenia		France, Netherlands
Consistency	0,96		1,00		1,00
Raw coverage	0,58		0,62		0,55
Unique coverage	0,07		0,11		0,07
Solution consistency		0,971			
Solution coverage		0,753			

Notes: * A= hr_c= Human resources
B= rs_c= Open, excellent and attractive research systems
C= fs_c= Finance and support
D= fi_c= Firm investments
E= la_c = Linkages & entrepreneurship = necessary condition (present in all sufficient conditions)
F= ia_c = Intellectual assets
** Finland, Sweden, Switzerland, Belgium, Denmark, Germany, Luxembourg and the UK were covered by more than one combination.

The analysis of sufficient conditions showed that the condition of Linkages & entrepreneurship was confirmed to be the only sufficient condition present in all solution paths to IUS success. This re-confirmed our original hypothesis that the condition of Linkages & entrepreneurship is necessary for innovation success (measured by a high IUS score).

The results also showed three combinations of sufficient conditions that lead to the presence of the outcome. So, while no individual condition is sufficient for high a IUS score, there are three combinations of sufficient conditions that are adequate.

4.1. Analysis of the robustness of results

In order to test the robustness of the three solution paths, we repeated the QCA procedure with small changes to the data calibration process and small changes to the raw consistency value. Both methods showed that our results were relatively robust. In most cases, using slightly different thresholds yielded relatively similar fuzzy scores as there were clear breaks in the original data, emphasised by the direct method of calibration.

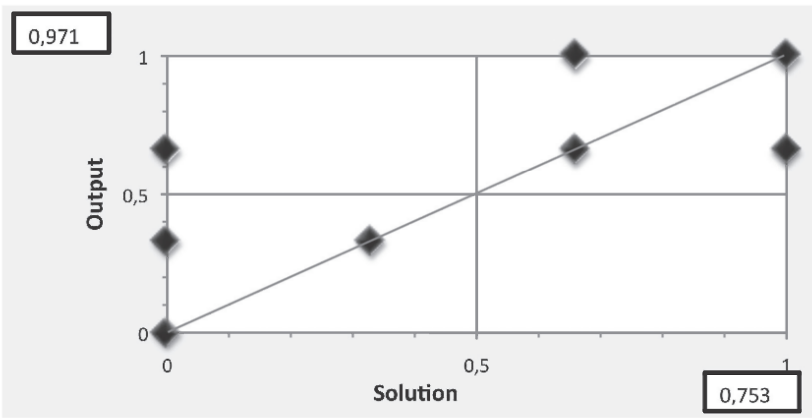
Similarly, in order to test the robustness of the truth table, we also tried to use the raw consistency threshold for the presence of the outcome of 0,8, as is often the standard in fsQCA analysis. It became obvious that a truth table obtained in this way has a significant problem. While consistency scores for rows 7 and 8 were higher than 0,8, their PRI scores were low – even 0 in the case of row 8. This showed that both sufficiency conditions are possibly also sufficiency conditions for the negated outcome ~Y. For that reason we decided to increase the consistency threshold to 0,99, where another clear break in the data assured no problems with the PRI scores. Thus, we obtained the original truth table presented above. Small changes to the consistency threshold of 0,99 did not change the structure of the truth table and had no effect on the results. Our results proved to be quite robust according to standard tests of robustness.

However, one problem with our QCA procedure was that it required a large number of prime implicants. This implied that we might have issues with limited diversity. In this case, we had only 23 observations (countries), but we had six conditions – meaning that there are 64 different combinations of conditions. Unfortunately, all the observations in our dataset have only filled 14 truth table rows, resulting in 50 logical reminders. It would help greatly if there were more observations and fewer logical reminders, so we plan to improve the dataset in the future with additional cases that will add to the variability. Nevertheless, there are no indications that additional observations would lead to significantly different solution paths. We therefore conclude that the results are quite robust.

4.2. Assessment of the quality of the results

While we obtained relatively robust results, they could still be of low quality in terms of explaining the actual cases of the countries. Luckily, the QCA analysis allowed us to formally test the quality of the solution. Both solution consistency scores and solution coverage scores are relatively high. That tells us that most of the countries (cases in our analysis) fit well into the three solution paths – their output (innovation success) is well predicted within our model. The plot of the solution shows that there is an overwhelming majority of typical cases that lie on the bisecting line and several irrelevant cases with very low solution outcomes. The plot also shows a single deviant case with a high solution score but a low outcome score: Estonia. This is a deviant case in terms of consistency in degree. This could imply that some conditions could be missing in the sufficiency path to explain the case of Estonia. Estonia is thus a good target for specific analysis in the form of a case study. On the other hand, we have another outlier in the form of Norway that has a high outcome score but a low solution score. It is thus a deviant case for coverage and could imply that the entire solution path could be missing. Again, this would be a good choice for a case study (although one can imagine that sufficient oil revenue and other broad innovation factors make Norway highly attractive for innovation).

Figure 1: *XY plot for the overall solution*



Notes: * *Solution consistency and solution coverage are reported in the corners.*

We can conclude that our solution has relatively high coverage and consistency values and that a large majority of cases lie on the bisecting line, representing typical cases for the solution. The solution is actually quite good at explaining the different sufficiency conditions leading to innovation success.

A general observation one can also ascertain from the XY solution plot is a clear clustering of countries. With the exception of Norway, all Scandinavian countries and Switzerland are successful and have good solution scores. On the other hand, Southern European countries as well as some Eastern European countries cluster together with low outcome scores and low solution scores – in the bottom left corner – and are thus irrelevant cases. A potential explanation for this might be that their low scores could be explained by special conditions. However, the QCA analysis requires a special analysis to explain the negation of the outcome (in this case, the absence of innovation success). We continued to perform the analysis for the negation of the outcome - ~Y = low Innovation Union Scoreboard Summary Index. While not presented here due to space limitations, it does shows conditions leading to a lack of innovation success different from the ones leading to its presence. Such asymmetric results are normal for the QCA method but are not possible to obtain using correlational statistical methods.

5. DISCUSSION

These results were already quite interesting for the evaluation of the methodology background of the IUS Summary Index. Our QCA analysis showed that the IUS Summary Index methodology is flawed as it lies on a foundation of the probabilistic method of regression analysis. The results of this method are not to be interpreted as if they reveal set relations, necessity or sufficiency. For example, the IUS Summary Index implies that if a country aims to increase individual innovation factors (conditions in QCA analysis), this would lead to a (marginal) increase in its IUS Summary Index score. However, our analysis showed that countries with high IUS Summary Index scores have used different and often specific paths and combinations of conditions to obtain their scores. It is not necessary to have high scores in all factors to reach the outcome. Similarly, in order to improve innovation success, missing conditions can impede achievement of overall success even if countries continue to increase other factors. Single innovation policy measures can unfold only in combination with other precisely specified conditions. In our case, an increase in the *Intellectual assets* score would not improve the overall innovation success of a country like Ireland or Slovenia as sufficient conditions for their innovation success are *Human resources* and *Firm investments* (as well as the necessary condition for all innovation success of *Linkages & entrepreneurship).* This confirmed conjunctural causation – a defining characteristic of causal complexity.

Another advantage of using a set-theoretic method in our research was that it enabled potential clusters of institutional configurations and countries to be identified. If such clusters could be found, this would imply convergence tendencies among countries. Additionally, this approach could lead to an observation that several different configurations of causal conditions will be linked to the same outcome (Allen & Aldred, 2011). This is very useful for our research as it allowed us to assess whether different countries are able to reach the same objective – innovation outputs – by different means. The results of our research showed three distinct paths to the outcome, each with specific countries that use it (there are also a number of countries that use more than one path at the same time). This confirmed equifinality – another characteristic of causal complexity.

Finally, the results showed that the paths to the outcome were not the same as the paths to the negation of the outcome. Three distinct paths exist to explain the combinations of sufficient conditions that lead to the presence of the outcome, and one condition is proven to be necessary. However, while not presented in the paper, four paths lead to the negation of the outcome and no condition is necessary. This is a clear example of causal asymmetry.

Our research showed that the phenomenon of successful innovation policy is causally complex. It also showed that the IUS Summary Index does not account for this complexity. The IUS Summary Index is inherently a correlation model. This method would be appropriate if the innovation theory implied (and empirical evidence confirmed) that the linear additive effects of single variables independent of any other causal factor would be sufficient to explain different levels of innovation outcomes between countries. As this does not seem to be the case and innovation policies are causally complex, set-theoretic methods are a better methodological model for research on innovation policies (Schneider & Wagemann, 2012, p. 77).

This does not mean that set-theoretic methods have no limitations. They are based on data calibration that influences set memberships. In general, slight changes in the calibration could lead to significantly different results. Its use of logical reminders to obtain maximum diversity and best results is difficult and often flawed (although one can always choose to ignore the use of logical reminders and just use the complex solution that does not include logical reminders in its analysis). And initially, the method is somewhat difficult to use as its logic rests on Boolean algebra and not on the probabilistic statistical approach that most social science researchers are more familiar with. However, the use of this novel method can improve the understanding of some phenomena that 'standard' statistical methods cannot explain well. We believe that innovation policy research is such a phenomenon.

6. CONCLUSION AND IMPLICATIONS

We have identified a couple of specific countries that call for more thorough in-depth analysis in the form of case studies. Our analysis identified Estonia and Norway as specific targets. Estonia has a high solution score but a low outcome score. This is a deviant case for consistency in degree. On the other hand, we have another outlier in the form of Norway, which has a high outcome score but a low solution score. It is thus a deviant case for coverage. Both cases are not well explained by the three solution paths obtained as results of the QCA procedure. They call for more in-depth analysis in the form of case studies.

The demonstration of the fsQCA procedure on our dataset also confirmed the special importance of *Linkages & entrepreneurship* as a necessary condition for innovation success. This supports the idea originating from the open innovation framework: Innovation is not a closed system but is rather dependent of the extent of mutual cooperation. A lack of linkages and networking across organisational boundaries does represent a systemic failure, as do lock-ins to specific collaboration partners, sources of ideas and information or excessive overall 'closure' of learning processes (Herstad et al., 2010). This failure needs to be tackled in a way similar to market failures – through policy intervention (Klein Woolthuis et al., 2005). Innovation policies need to take this into account and devise policy measures that do not focus solely on supporting individual companies but on their collaboration as well.

Examples of such policies are already in place. In the EU, they include the Knowledge and Innovation Communities (KIC) of the European Institute of Innovation and Technology

(EIT). They focus on the international collaboration of companies, public research organisations, universities and other actors from several EU countries in pursuit of the development of a specific technology (and creating pan-European value chains for the future). The results of these policies are measured in the IUS by public–private co-publications, innovative SMEs collaborating with others and SMEs innovating in-house. R&D collaboration (especially international) and joint entrepreneurial development of new innovations form the necessary condition for innovation success and should be targeted by national policy-makers. Another interesting example of such a policy instrument is the so-called 'innovation voucher' – successfully implemented in the US and in Israel. Companies can obtain a subsidy from the government that has to be used for obtaining innovation results (often technology or intellectual property) from public research organisations. Thus, it facilitates mutual cooperation and knowledge transfer between public research (often in the realm of basic science) and commercialisation in private companies. Both private and public stakeholders benefit from such collaboration, as does the general public due to increased societal yields of public funds invested into basic public research in the form of newly created value. While this value is captured by the companies, it also contributes towards financing public goods through taxes and social contributions (and often licence fees).

However, there is no single public policy supporting Linkages & entrepreneurship that will be successful in every business (eco)system. While good practice examples as the ones mentioned above should be tried in several countries, the results of our analysis show that there are different solution paths leading to innovation success. This means that individual countries with their distinct business systems will be more inclined to try certain policies than others and will also be able to benefit more from certain policy measures than from others. This leads to the individual solution paths towards innovation success. Countries with similar business systems will develop similar solution paths, which we can observe in our results. This also means that individual countries should not blindly copy measures that work in other countries. Rather, they should test different measures and keep those that yield the best results, establishing their own solution paths. Successful innovation policy-making should be focused on establishing a platform for testing and evaluating different innovation policy measures, continuing those that are proven successful and discontinuing those that are not – replacing them with new measures to test. Such a lean policy-making approach mimics the lean approach to business development seen in startup companies.

Our research shows that the IUS framework remains useful as it provides data for a comparative assessment of research and innovation performance, collecting a large database of innovation indicators and innovation policy measures. This makes it a useful tool for innovation research. The IUS also highlights the importance of innovation policy to policy-makers and the general public, assuring innovation policies considerable publicity in the media and in the interested public. It has been instrumental in the preparation of the new pan-European flagship initiative called the 'Innovation Union' as part of the EU's 10-year strategy. However, the IUS Summary Index should not be recommended as a tool for innovation policy evaluation.

Finally, the results of our research revealed the specific limitations of our research. This research has the potential to expand its use by continuing with specific in-depth case studies, focusing on individual innovation policy measures and exploring the institutional structure and framework conditions for innovation.
Another clear limitation of this research is that it does not focus on evaluating particular and individual innovation policy measures. This was not its purpose, but such evaluation would be highly useful for a better understanding of the distinct causally complex processes that lead to innovation success. The EU, with its commonalities (shared cultural and to some extent regulatory environment) and differences in implementing national innovation policies represents a perfect laboratory for innovation policy research. There is also a sufficient amount of data gathered on EU countries, both on policy measures and their results. Further research in this direction would help explain large differences in innovation success between countries sharing so much otherwise.

Further studies on the broader innovation policies and institutional framework supporting innovation will also need to focus on the influence that these policies have on innovation success. For example, the 'varieties-of-capitalism' (Hall & Soskice, 2001) approach shows that the institutional structures of different types of economies influence their innovation capabilities and innovation success. We did not include such conditions in our analysis, but they could yield interesting results.

There is also clear evidence that socio-economic factors are increasingly important for the positioning of innovation activities in global value chains. Looking at 'narrow' innovation policies (those that specifically target innovation activities) might not be sufficient as other framework conditions might be even more important. A thorough analysis of the factors influencing innovation success will have to include them as well into the research design and dataset.

REFERENCES

Adam, F. (2014). *Measuring National Innovation Performance*. Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-39464-5

Allen, M. M. C., & Aldred, M. L. (2011). Varieties of capitalism, governance, and high-tech export performance: A fuzzy-set analysis of the new EU member states. *Employee Relations*, 33 (4), 334–355. doi:10.1108/01425451111140622

Arnold, E. (2004). Evaluating research and innovation policy: a systems world needs systems evaluations. *Research Evaluation*, 13 (1), 3–17. doi:10.3152/147154404781776509

Cherchye, L., Moesen, W., & Van Puyenbroeck, T. (2004). Legitimately Diverse, yet Comparable: On Synthesizing Social Inclusion Performance in the EU. *JCMS: Journal of Common Market Studies*, 42 (5), 919–955. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.0021-9886.2004.00535.x/abstract

Chesbrough, H. (2012). Open Innovation: Where We've Been and Where We're Going. *Research-Technology Management*, 55 (4), 20–27. doi:10.5437/08956308X5504085

Chesbrough, H. W. (2003). *Open innovation: the new imperative for creating and profiting from technology* (p.

227). Harvard Business Press. Retrieved from http://books.google.com/books?hl=en&lr=&id=4hTRWStFhVgC&pgis=1

Chesbrough, H. W. (2006). *Open Business Model* (p. 256). Boston: Harvard Business Press. Retrieved from http://books.google.si/books?id=-f4XSIN37coC&dq=open+business+models&source=gbs_navlinks_s

Commission, E. (2013a). DG Enterprise and industry - Industrial Innovation. *European Commission web portal*. Retrieved from http://ec.europa.eu/enterprise/policies/innovation/

Commission, E. (2013b). DG Enterprise and industry - Innovation Policy. *European Commission web portal*.

Commission, E. (2013c). Innovation Union - a Europe 2020 Initiative. *European Commission web portal*. Retrieved from http://ec.europa.eu/research/innovation-union/index_en.cfm

De Backer, K. et al. (2008). *Open innovation in Global Networks* (Vol. 14, p. 132). Paris. doi:10.1016/j.drudis.2009.09.001

Diez, M. A. (2001). The Evaluation of Regional Innovation and Cluster Policies: Towards a Participatory Approach. *European Planning Studies, 9*(7), 907–923. doi:10.1080/09654310120079832

Ebersberger, B., Herstad, S., Iversen, E., Kirner, E., & Som, O. (2011). *A NALYSIS OF INNOVATION DRIVERS AND BARRIERS Economic and Market Intelligence on Innovation Open Innovation in Europe : effects , determinants and policy. Innovation* (p. 235).

Economist, I. U. (2009). *A new ranking of the world ' s most innovative countries: notes on methodology* (p. 11). London.

Edquist, C. (2001). The Systems of Innovation Approach and Innovation Policy: An account of the state of the art. *DRUID Conference, Aalborg*, 1–24. Retrieved from http://www.druid.dk/uploads/tx_picturedb/ds2001-178.pdf

Fiss, P. (2011). Building better causal theories: a fuzzy set approach to typologies in organization research. *Academy of Management Journal*, 54 (2), 393–420.

Fiss, P. (2012). Using Qualitative Comparative Analysis (QCA) and Fuzzy Sets.

Hall, P. A., & Soskice, D. (2001). *Varieties of capitalism: The institutional foundations of comparative advantage* (p. 540). New York: Oxford University Press.

Herstad, S. J., Bloch, C., Ebersberger, B., & van de Velde, E. (2010). National innovation policy and global open innovation: exploring balances, tradeoffs and complementarities. *Science and Public Policy*, 37 (2), 113–124. doi:10.3152/030234210X489590

Hollanders, H., Es-Sadki, N., & Commission, E. (2013). *Innovation Union Scoreboard 2013. The Innovation Union's performance scoreboard for ...* (p. 80). Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Innovation+Union+Scoreboard#1

Hollanders, H., & van Cruysen, A. (2008). *Rethinking the European Innovation Scoreboard: A New Methodology for 2008-2010* (p. 44).

Irish Innovation Taskforce. (2010). *Innovation Ireland - Report of teh Innovation Taskforce* (p. 132). Dublin.

Klein Woolthuis, R., Lankhuizen, M., & Gilsing, V. (2005). A system failure framework for innovation policy design. *Technovation*, 25 (6), 609–619. doi:10.1016/j.technovation.2003.11.002

Kraemer, K. L., Gurbaxani, V., & King, J. L. (1992). Economic development, government policy, and the diffusion of computing in Asia-Pacific countries. *Public Administration Review*, 52 (2), 146–156.

Lin, G. T. R., Shen, Y.-C., & Chou, J. (2010). National innovation policy and performance: Comparing the small island countries of Taiwan and Ireland. *Technology in Society*, 32 (2), 161–172. doi:10.1016/j.techsoc.2010.03.005
Mcphee, C., & Segers, J. (2013). Editorial: Open Innovation and Entrepreneurship. *Technology Innovation Management Review*, (April), 3–5.

Nill, J., & Kemp, R. (2009). Evolutionary approaches for sustainable innovation policies: From niche to paradigm? *Research Policy*, 38 (4), 668–680. doi:10.1016/j.respol.2009.01.011

OECD Reviews of Innovation Policy: Slovenia. (2012) (p. 182).

OECD Science, Technology and Industry Scoreboard 2013. (2013) (p. 279). doi:http://dy.doi.org/10.1787/sti_scoreboard-2013-en

Ragin, C. C. (1987). *The comparative method* (p. 181). University of California Press.

Ragin, C. C. (2000). *Fuzzy-set social science* (p. 350).

Ragin, C. C. (2007). *Družboslovno raziskovanje - enotnost in raznolikost metode* (p. 201).

Ragin, C. C., Kriss, A. D., & Davey, S. (2006). Fuzzy-Set/Qualitative Comparative Analysis 2.0. Tuscon, Arizona: University of Arizona, Department of Sociology.

Ragin, C. C., & Rihoux, B. (2009). *Configurational Comparative Methods* (p. 185).

Rammer, C., & (ZEW), C. for E. E. R. (2005). *Comments on EIS Improvements for 2005*.

Rihoux, B., & Grimm, H. (2006). *Innovative Comparative Methods for Policy Analysis* (p. 358). Springer.

Schibany, A., & Streicher, G. (2008). The European Innovation Scoreboard: drowning by numbers? *Science and Public Policy*, 35 (10), 717–732. doi:10.3152/030234208X398512

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic Methods for the Social Sciences* (p. 350).

Svarc, J. (2006). Socio-political factors and the failure of innovation policy in Croatia as a country in transition. *Research Policy*, 35 (1), 144–159. doi:10.1016/j.respol.2005.09.002

Švarc, J. (2006). Socio-political factors and the failure of innovation policy in Croatia as a country in transition. *Research Policy*, 35 (1), 144–159. doi:10.1016/j.respol.2005.09.002

Technology, P. C. O. A. O. S. A. (2010). *Report to the President and the Congress on the Third Assessment of the National Nanotechnology Initiative* (Vol. 4, p. 96). Washington.

Von Hippel, E. (1986). Lead Users: A Source of Novel Product Concepts. *Management Science*, 32 (7), 791–805. doi:10.1287/mnsc.32.7.791

Von Hippel, E. (2005). *Democratizing innovation*.

APPENDIX

Raw data

2010 VALUES (ORIGINAL NORMALISED VALUES)	**Summary Innovation Index**	Human resources	Research systems	Finance and support	Firm investments	Linkages & entrepreneurship	Intellectual assets
Belgium	**0,625**	0,657	0,761	0,597	0,471	0,733	0,511
Czech Republic	**0,400**	0,509	0,283	0,294	0,419	0,429	0,257
Denmark	**0,704**	0,633	0,777	0,674	0,564	0,813	0,875
Germany	**0,711**	0,605	0,544	0,597	0,695	0,629	0,799
Estonia	**0,492**	0,532	0,326	0,646	0,631	0,607	0,349
Ireland	**0,571**	0,746	0,631	0,359	0,501	0,533	0,446
Greece	**0,339**	0,450	0,298	0,206	0,220	0,466	0,138
Spain	**0,410**	0,405	0,539	0,497	0,264	0,261	0,401
France	**0,540**	0,670	0,656	0,656	0,349	0,470	0,477
Italy	**0,429**	0,426	0,398	0,386	0,438	0,305	0,517
Luxembourg	**0,651**	0,747	0,534	0,635	0,505	0,547	0,647
Hungary	**0,333**	0,430	0,246	0,262	0,324	0,203	0,267
Netherlands	**0,595**	0,631	0,820	0,710	0,235	0,585	0,679
Austria	**0,626**	0,581	0,613	0,498	0,502	0,743	0,753
Poland	**0,304**	0,584	0,153	0,338	0,313	0,187	0,243
Portugal	**0,426**	0,438	0,447	0,549	0,417	0,356	0,346
Slovenia	**0,499**	0,602	0,410	0,542	0,557	0,602	0,425
Slovakia	**0,322**	0,563	0,160	0,146	0,460	0,205	0,168
Finland	**0,708**	0,877	0,593	0,832	0,639	0,900	0,643
Sweden	**0,766**	0,880	0,795	0,911	0,666	0,849	0,788
United Kingdom	**0,599**	0,698	0,784	0,749	0,470	0,551	0,469
Norway	**0,485**	0,663	0,817	0,656	0,213	0,567	0,305
Switzerland	**0,818**	0,820	1,000	0,666	0,713	0,709	0,952

Calibrated data

	Summary Innovation Index	Human resources	Research systems	Finance and support	Firm investments	Linkages & entrepreneurship	Intellectual assets
country	ius_c	hr_c	rs_c	fs_c	fi_c	la_c	ia_c
BE	0,94	0,96	1	0,72	0,85	1	0,57
CZ	0,25	0,6	0,06	0,04	0,64	0,61	0,04
DK	0,99	0,94	1	0,9	0,98	1	1
DE	0,99	0,9	0,81	0,72	1	0,99	1
EE	0,56	0,69	0,11	0,85	1	0,99	0,12
IE	0,85	0,99	0,96	0,09	0,92	0,94	0,34
GR	0,12	0,37	0,08	0,02	0,05	0,78	0,01
ES	0,27	0,24	0,79	0,37	0,1	0,08	0,22
FR	0,76	0,97	0,97	0,87	0,31	0,79	0,44

	Summary Innovation Index	Human resources	Research systems	Finance and support	Firm investments	Linkages & entrepreneurship	Intellectual assets
IT	0,33	0,3	0,26	0,13	0,73	0,15	0,6
LU	0,96	0,99	0,77	0,83	0,93	0,95	0,94
HU	0,11	0,31	0,04	0,03	0,23	0,03	0,04
NL	0,9	0,93	1	0,94	0,06	0,98	0,97
AT	0,94	0,85	0,94	0,37	0,92	1	0,99
PL	0,08	0,86	0,01	0,07	0,2	0,03	0,03
PT	0,32	0,33	0,42	0,53	0,62	0,29	0,12
SI	0,59	0,89	0,3	0,5	0,98	0,99	0,28
SK	0,1	0,8	0,01	0,01	0,82	0,03	0,01
FI	0,99	1	0,91	0,99	1	1	0,94
SE	1	1	1	1	1	1	1
UK	0,9	0,98	1	0,97	0,85	0,96	0,41
NO	0,53	0,96	1	0,87	0,04	0,97	0,07
CH	1	1	1	0,89	1	1	1

Fuzzy scores

	Summary Innovation Index	Human resources	Research systems	Finance and support	Firm investments	Linkages & entrepreneurship	Intellectual assets
BE	1	1	1	0,66	0,66	1	0,66
CZ	0,33	0,33	0	0	0,66	0,66	0
DK	1	0,66	1	1	1	1	1
DE	1	0,66	0,66	0,66	1	1	1
EE	0,66	0,33	0	1	1	1	0,33
IE	1	1	1	0	0,66	1	0,33
GR	0	0	0	0	0	0,66	0
ES	0,33	0	0,66	0,33	0	0	0,33
FR	0,66	1	1	1	0,33	0,66	0,66
IT	0,33	0	0,33	0	0,66	0,33	0,66
LU	1	1	0,66	1	0,66	1	1
HU	0	0	0	0	0,33	0	0
NL	1	0,66	1	1	0	1	1
AT	1	0,66	1	0,33	0,66	1	1
PL	0	0,66	0	0	0,33	0	0
PT	0,33	0	0,33	0,33	0,66	0,33	0,33
SI	0,66	0,66	0,33	0,33	1	1	0,33
SK	0	0,33	0	0	0,66	0	0
FI	1	1	1	1	1	1	1
SE	1	1	1	1	1	1	1
UK	1	1	1	1	0,66	1	0,66
NO	0,66	1	1	1	0	1	0
CH	1	1	1	1	1	1	1