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Measuring regional innovation in one dimension: More lost than gained?

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Abstract

In both academic literature and political discussions the concept of innovation is recognized as an essential ingredient in economic development and competitiveness for firms, regions, and nations. Innovation also ranks at the top of policy agendas in the field of regional policy. Therefore, the attractiveness of an appropriate innovation index for ranking regions and further developing them along a more or less objective measurement scale is evident. However, whether such rankings help convey a better understanding of innovation and its drivers, or whether they are merely a special type of 'beauty contest' with little substance is the focus of our analyses. To deny the latter, the innovation output indicators used for the composite index have to be appropriate representatives of the underlying innovation concept and each indicator has to be driven by the same impact factors. If this is not the case, interpretation of the index inevitably gives rise to partly inappropriate policy recommendations. In order to demonstrate this claim we elaborate a set of innovation indicators at the regional level based on the theoretical concept of the OECD document 'The Measurement of Scientific and Technological Activities, Proposed Guidelines for Collecting and Interpreting Technological Innovation Data' known as the 'Oslo Manual' (OECD, 2005) and their empirical implementation in the Community Innovation Survey. Additionally, innovation drivers well established in the literature are collected to estimate their impact on each innovation indicator as well as on the composite index derived from the innovation indicators. The question whether

innovation should be measured as a multidimensional concept and investigated using various indicators or whether simplifying innovation to a one-dimensional concept is appropriate is clearly answered in favour of the multidimensional approach. Surprisingly, this is not due to the multidimensionality of the indicators themselves (all statistical measures indicate that the considered variables are sufficiently represented by one component), but to our first evidence that the innovation output indicators are driven by various impact factors and can therefore be influenced by various political strategies. According to these findings any type of innovation ranking is of very limited use.

Highlights

- Innovation indicators are driven by various input factors.
- Innovation indicators are not appropriate for composite index construction.
- Innovation is a multidimensional concept.
- Popular composite indices are of limited use for regional policy.

1. Introduction

Although innovation is a key subject in regional economic research (Asheim et al., 2011; Cooke et al., 1997; Simmie, 2004) and at the centre of attention in current discussions of economic policy (European Commission, 2005, 2010), there is no generally accepted concept regarding the operationalization of this phenomenon. This is even more surprising given the extensive scientific debate on suitable innovation indicators (Archibugi, 1992; Griliches, 1990; Kleinknecht et al., 2002; Smith, 2005). Furthermore, clear conceptualization is essential in order to understand driving forces and effects of innovation processes at the regional level. The present work aims to make a contribution to this discussion.

Current empirical literature on regional innovation primarily focuses on three approaches, all of them proposing one measure for the level or type of innovation. The first and probably most frequently used method is to measure innovative activities using a single indicator. Patent statistics (Bilbao-Osorio and Rodriguez-Pose, 2004; Bottazzi and Peri, 2003; Buesa et al., 2010; Cabrer-Borrás and Serrano-Domingo, 2007; Hauser et al., 2007; Moreno et al., 2005; Moreno et al., 2006) and indicators derived from such data, e.g. patent citations (Maurseth and Verspagen, 2002; Paci and Usai, 2009), dominate this group. More recently, in order to directly address newly introduced innovations, information on new product announcements was collected from technical and trade journals (Acs et al., 2002; Coombs et al., 1996). However, the time-consuming process of data collection has prevented this procedure from playing a major role to date.

The second group of approaches is based on a multitude of innovation indicators and combines them directly or stepwise to form a single index. The best known example of this methodology is the Innovation Scoreboard, that at both the national and the regional level generates an innovation performance index based on indicators referring to three pillars (enablers, firm activities, outputs) (Hollanders and Es-Sadki, 2014; Hollanders et al., 2014). Special cases are factorisations, contrary to the afore-mentioned one, that endogenously compute the weights of the indicators.

The third group of approaches for analysing regional innovation also employs an extensive set of indicators. These indicators provide the basis for the clustering of regions and are used to identify regional innovation regimes (Ajmone Marsan and Maguire, 2011; Capello and Lenzi, 2013; Navarro et al., 2009). In opposition to the first two groups, these studies emanate from a multidimensional innovation concept allowing typologies of a diversity of innovation regimes (for details on territorial innovation approaches, see (Asheim et al. (2011); Camagni (1995); Cooke et al. (1997); Crevoisier (2004)). In this way this approach achieves the greatest flexibility.

However, all approaches show clear limitations. These issues are particularly discussed for patent statistics. Regarding this data it has been shown that some aspects of innovation are not captured at all or only to an incomplete extent. A key limitation of patent statistics is that they primarily cover inventions and not commercial innovations (Smith, 2005), while reflecting innovative activities of different sectors very differently (Blind et al., 2006; Brouwer and Kleinknecht, 1999; Cohen et al., 2000; Harabi, 1995; Levin et al., 1987). The ability of patent data to reflect service innovations (Blind et al., 2003; Hipp and Grupp, 2005) and process innovations (Arundel and Kabla, 1998; Blind et al., 2003; Brouwer and Kleinknecht, 1999; Cohen et al., 2000) is also limited. The critique of all unidimensional approaches originates from the assumption that a single indicator can impossibly reflect the complex innovation phenomenon.

The second approach can not completely dismiss this critique, because the many considered indicators ultimately form a single index and, even more problematically, enter as unidimensional the political discourse. The use of an index is reasonable only if all underlying indicators are correlated to such an extent that they can be interpreted as indicators of an unobservable phenomenon. However, composite indices often combine input variables and output indicators. Therefore, causes and effects of innovation are no longer separable.

Even though the third approach uses input variables and output indicators contemporaneously, it is less problematic because it does not focus on innovation performance rankings – suggesting in this way a monotonic order of innovation levels - but on typologies of innovation regimes. Although the categorical quality of innovation regimes allows a high degree of flexibility, it ends up with a unidimensional categorization. Therefore, this approach is appropriate for a categorization of innovation regimes, but hardly appropriate for analysing the effects of driving forces on innovation dynamic.

In this context, the present article seeks to evaluate whether a single index can sufficiently represent innovation, perceived as the output of innovation processes. In order for this to be possible two requirements must be fulfilled: First, all underlying indicators measuring innovation outcomes need to be sufficiently correlated, so they can be interpreted as indicators for a latent innovation construct. Second, the inevitable loss of information caused by aggregating individual indicators to one main component should not mask essential characteristics of the innovation dynamic. If all innovation indicators are driven by the same input variables in a similar way, innovation indicators can be comprised in a one-dimensional concept. Otherwise, the aggregation possibly obscures important instruments for innovation policy.

The following steps address the research question:

- We elaborate a set of innovation indicators at the regional level based on the theoretical principles of the OECD document 'The Measurement of Scientific and Technological Activities, Proposed Guidelines for Collecting and Interpreting Technological Innovation Data' known as the 'Oslo Manual' (OECD, 2005) and their empirical implementation in the Community Innovation Survey. This systematization of innovation captures different, possibly independent, aspects of regional innovation output. The first step investigates the existence of multiple innovation dimensions as well as the question whether creating a single innovation component using principal component analysis (PCA) is suitable. The derived components are interpreted as indicators of innovation output with endogenously obtained weighting of the single indicators.
- Subsequently, groups of innovation input variables – presumed to drive the innovation output - are identified from the literature. Suitable variables are selected for each group.
- Finally, we analyse the impact of the input variables on the different innovation output indicators as well as on the derived components. This approach is chosen to investigate whether or not all input variables influence all innovation output indicators in a similar way.

This will shed light on the potentials and limitations of the use of composite indices in regional innovation research.

This article is organized as follows: Section 2 illustrates the frame of the analyses. Section 3 describes the data used and the correlated transformation processes. The empirical results are presented in Section 4, and Section 5 discusses these results and proposes some conclusions.

2. Frame of the analyses

The Oslo Manual (OECD, 2005) provides a comprehensive framework for the classification of innovation according to four principal dimensions. Firstly, innovation is classified by type. Technological innovations pertain to product and process innovations, whereby product innovations are further differentiated into goods and services innovations. Secondly, according to their level innovations are distinguished as novelties for the firm or novelties for the market. Finally, innovations are also characterized with regard to their economic success (successful or not). The systematization of these dimensions obtains the innovation classification framework illustrated in Table 1, clearly comprising twelve different aspects for the analysis of innovation.

Table 1

Classification of innovation aspects numbered 1 to 12, as suggested by the Oslo Manual (OECD, 2005)

		Firm novelty		Market novelty	
		no success	success	no success	success
Products	Goods	1	2	3	4
	Services	5	6	7	8
Processes		9	10	11	12

All four dimensions are mutually exclusive and exhaustive. However, for the sake of completeness it should be noted that the literature also identifies marketing and organisational innovations (OECD, 2005). Whether all of these 12 aspects are manifestations of the same latent innovation construct or not, is the main question of this paper. Unfortunately, finding indicators that accurately reflect one and only one of the twelve innovation aspects is difficult.

This can be easily shown by checking the patent variable. Since patent protection demands certain standards of novelty and originality, this indicator does not capture the innovation aspects on the left side of Table 1 (fields numbered 1, 2, 5, 6, 9, and 10). Furthermore, the literature suggests that these data reflect the remaining aspects to varying extents. Consequently, the indicator covers market novelties in the form of goods innovations well (3 and 4). However, the remaining fields on the right side of the table are covered only moderately (7, 8, 11, and 12) since the indicator does not provide information on the economic success of innovations and service or process innovations are less likely to be patented than are goods innovations. In addition, innovations of types 3 and 4 exist that are not patentable or not patented for financial, firm-strategic, cultural or other reasons (Cohen et al., 2000; Hussinger, 2006).

Data at the regional level representing different aspects of innovation along the classification of Table 1 can be obtained from the European Community Innovation Survey (CIS). Table 2 shows indicators selected for the present analyses attempting to capture the aspects of Table 1. Table 2 shows which innovation aspects should presumably be covered by the individual regional innovation indicators.

Table 2

Regional innovation indicators derived from the Community Innovation Survey and Eurostat Regio Database

Name	Source	Description (aggregated indicator[a])	Innovation aspects (Table 1)
Goods innovators	CIS2008	% of goods innovators	1, 2, 3, 4
Service innovators	CIS2008	% of service innovators	5, 6, 7, 8
Process innovators	CIS2008	% of process innovators	9, 10, 11, 12
New-to-firm product innovators	CIS2008	% of new-to-firm product innovators	1, 2, 5, 6
New-to-market product innovators	CIS2008	% of new-to-market product innovators	3, 4, 7, 8
Turnover share of new-to-firm product innovations	CIS2008	Mean turnover share of new-to-firm product innovations	2, 6
Turnover share of new-to-market product innovations	CIS2008	Mean turnover share of new-to-market product innovations	4, 8
Patent applications	Eurostat	Patent applications per million inhabitants	3, 4, 7, 8, 11, 12

Notes:

[a] Aggregation method: Binary CIS indicators result in regional share (percentage) of firms that introduced the respective innovation type (or novelty degree of innovations); turnover share variables are aggregated to the mean turnover share of innovative products over all firms in a region. The patent indicator is standardized with the number of million inhabitants of the region.

Amongst the constructed innovation output indicators both indicators referring to the turnover share of newly introduced innovations have an exceptional position. In contrast to the other indicators, they potentially capture the market success of an innovation. In this sense they represent innovation in contrast to inventions.

In order to analyse whether the eight innovation output indicators are influenced by the same determinants in a similar way, a set of potential drivers of innovation output is needed.

Our selection of innovation drivers is largely based on the existing literature, particularly referring to the concept of the knowledge production function (Griliches, 1979). The following groups of drivers are considered: human capital (Dakhli and De Clercq, 2004; Fritsch and Slavtchev, 2007; Lund Vinding, 2006), expenditures for R&D efforts (Acs et al., 2002; Bilbao-Osorio and Rodriguez-Pose, 2004; Buesa et al., 2010; Crescenzi et al., 2013; Doh and Acs, 2010; Hauser et al., 2007; Rodríguez-Pose and Crescenzi, 2008), the quality of institutions (Barbosa and Faria, 2011; Knack and Keefer, 1995; Rodríguez-Pose, 2013; Rodrik et al., 2004), social capital (Crescenzi et al., 2013; Doh and Acs, 2010; Hauser et al., 2007; Landry et al., 2002), culture (Herbig and Dunphy, 1998; Kaasa and Vadi,

2010) as well as the economic structure of the respective region (Bilbao-Osorio and Rodriguez-Pose, 2004; Greunz, 2004).

Although we capture a wide range of drivers, it is not the aim of this paper to exhaustively model the relations to innovation output. The approach employed here aims to assess whether or not the inputs affect the innovation output indicators in a similar way. Figure 1 shows the structure of the coherences under investigation.

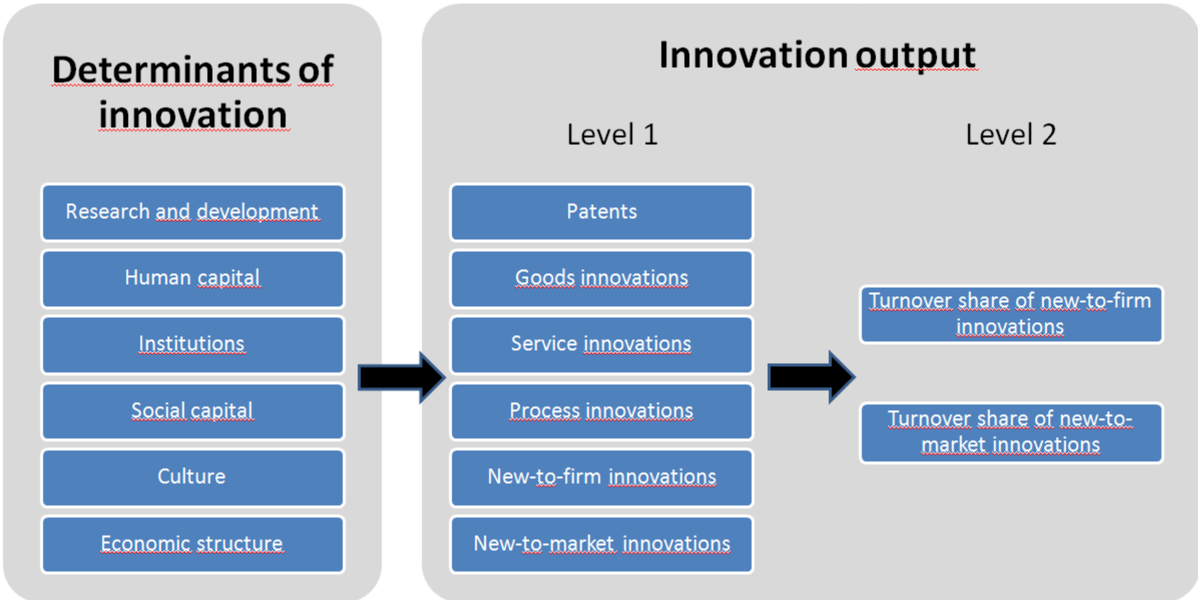

Figure 1
The literature shows relevant groups of input variables for the two levels of innovation indicators.

Working from the framework illustrated in Figure 1 we first examine how many independent dimensions are identified when applying principal component analysis (PCA) to the innovation output indicators, how the arising components can be interpreted and how efficient the PCA uses the information incorporated in the components.

We then use regression analysis to study whether or not the individual innovation output indicators and the derived components resulting from the PCA are influenced by the same input variables. We employ a spatial econometric approach in order to account for the presence of spatial effects.

3. Data selection and transformations

All but one innovation output indicators are constructed from the CIS. The exception is the patent indicator (average yearly number of patent applications per million inhabitants during the period 2006 to 2008), which is derived from Eurostat's regional database. The CIS is a periodic survey and collects input and output information on the innovation activities of European firms over a three-year period. The survey is conducted in European Union member states plus Iceland, Norway, Serbia and Turkey. The harmonized survey methodology follows the Oslo Manual (OECD, 2005)[1]. We derive the data from the sixth wave (CIS2008) of the survey, which covers the observation period from 2006 to 2008. Given that the CIS data are available only for a subset of European regions, we compose a final dataset of 104 regions.[2] Due to the varying regional CIS sample sizes in different countries, the levels of analysis are chosen as a combination of regions ranked NUTS1[3] (Bulgaria (2), Germany (16), Ireland (1), Estonia (1), France (8), Latvia (1), Lithuania (1), the Slovak Republic (1), Slovenia (1), Spain (6), and the United Kingdom (12))[4] and NUTS2 (Austria (9), the Czech Republic (8), Denmark (5), Finland (4), Poland (15), Portugal (5), and Romania (8)). The data for Germany, the Czech Republic, Denmark, France, Spain, Portugal, and the United Kingdom are based on the NACE[5] Rev. 2 divisions for CIS core and additional coverage[6], as set out in the CIS2008 methodological recommendations, whereas the data for the remaining territorial units include only the CIS core-coverage industries. Moreover, the CIS indicators referring to Bulgaria are based on small and medium enterprises (i.e. up to 249 employees), whereas data for all other regions also include large enterprises[7].

We elaborate the eight indicators reflecting regional innovation output shown in Table 2. To eliminate size as a possible source of distortion, we include the CIS indicators as percentages and patent data are standardized per million inhabitants of a region. All CIS-based indicators are constructed on the firm level and then aggregated on the regional level (see Table A.1 in the Appendix for detailed information on the construction of firm-level CIS indicators). Consequently, we calculate five CIS indicators as the percentage of population giving positive answers to the respective questions. The two indicators referring to the realized turnover share of innovative products were included as regional unweighted average percentages.

The data used for the second part of the present analysis refer to potential driving forces of innovation. First, we collect variables for each of the six groups, i.e. *R&D*, *Human Capital*, *Institutions*, *Social Capital*, *Culture*, and *Economic Structure*. We predominantly retrieve this data from Eurostat.

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[1] For metadata and methodological issues see: http://ec.europa.eu/eurostat/cache/metadata/en/inn_cis2_esms.htm.

[2] Since CIS data with appropriate NUTS codification are not available as a central database, these data were collected separately from national statistics offices with varying access procedures. In our view the difficulty of accessing data is a major reason why the valuable CIS data have practically no role in regional innovation research, with the exception of the highly transformed Regional Innovation Scoreboard indicators.

[3] Eurostat's *Nomenclature of territorial units for statistics* (NUTS) classification divides the European economic territory for statistical and analytical purposes. For more information see: http://ec.europa.eu/eurostat/web/nuts/overview.

[4] For Ireland, Estonia, Latvia, Lithuania, Slovakia and Slovenia the country level corresponds to the NUTS1 level.

[5] *Nomenclature statistique des activités économiques dans la Communauté européenne* (NACE) is the classification system for European industries. For more information see: http://ec.europa.eu/eurostat/web/nace-rev2.

[6] According to the CIS methodological recommendations the following NACE Rev. 2 divisions refer to CIS core coverage: 05-09, 10-33, 35, 36-39, 46, 49-53, 58, 61, 62, 63, 64-66, 71. Additional coverage includes the following NACE Rev. 2 divisions: 41-43, 45, 47, 55-56, 59-60, 68, 69, 70, 72, 73, 74, 75, 77, 78, 79, 80, 81, 82. Agriculture and forestry and fishing (NACE Rev. 2 divisions: 01-03) are excluded from the present analysis.

[7] The stability of the results with respect to limitation to core-coverage industries is checked. PCA is computed for the same regions using data for only core industries and data for all available industries. The findings are qualitatively very similar.

Exceptions are the European Quality of Government Index (EQI) developed by Charron et al. (2014) and the variables for the construction of *Social Capital* and *Culture*. *Social Capital* and *Culture* are both seen as latent concepts and operationalized based on household surveys applying factor-analytical methods.

Indicators of the *Social Capital* proxies were developed from questions on attitudes towards and networks of social interaction in the European Values Study[8]. In order to maximise sample size for each region we pool the responses from the second (1990), third (1999) and fourth (2008) waves of the survey. Given that *Social Capital* is formed over the time span of centuries (Putnam et al., 1993) and thus highly persistent over time (Guiso et al., 2008), such a pooling of data provides the most informative indicator for endowments with *Social Capital* in various regional cultures. Regarding the concept of *Social Capital* we follow the methods of Hauser et al. (2007) and Bjørnskov (2006). We identify the different dimensions by applying a PCA with a Varimax rotation to eight variables taken from the EVS2008 in order to account for the multidimensionality of *Social Capital*. As suggested by Puntscher et al. (2014), the PCA is applied to regionally aggregated data in order to avoid misleading aggregation effects. The PCA extracts three independent components. The first component is termed 'Strong Ties' since this component is most strongly associated with the importance of close relationships such as family or friends, whereas the second component is labelled 'Weak Ties and Social Trust' and describes engagement in associational activities as well as general trust. The third component describes 'Political Interest' as an indicator for engagement with civil society.

Following Inglehart and Baker (2000) and Inglehart and Welzel (2010) the dimensions of the latent concept *Culture* are also obtained by applying a PCA with Varimax rotation to eight regionally aggregated variables from the pooled waves of the EVS data. The PCA extracts two independent components termed 'Traditional vs. Secular-rational Values' and 'Survival vs. Self-Expression Values'. The first dimension describes changes linked with the transition from agrarian to industrial society, associated with bureaucratization, rationalization, and secularization. The latter refers to polarization between emphasis on order, economic security, and conformity and emphasis on self-expression, participation, subjective well-being, trust, tolerance, and quality of life concerns (Inglehart and Welzel, 2010).

Tables A.2 and A.3 in the Appendix provide information on the EVS variables used for the construction of *Social Capital* and the dimensions of *Culture* and on the achieved statistical quality criteria.

Due to a high degree of multicollinearity, it is not possible to analyse the impact that the selected driving forces have on innovation using all considered input variables. This would lead to extremely

[8] For more information on the EVS, see: http://www.europeanvaluesstudy.eu/.

unstable estimates and inflated standard errors. We deal with this problem by applying two different approaches with the aim to include as much independent information as possible within and between the considered groups of determinants. Where multicollinearity is caused by bivariate correlations of two variables, one of these variables is excluded from the dataset (if possible, the theoretically more weakly founded variable). This means that the impact of a specific driving force may totally or partially rest on the excluded variable. However, this does not constitute a problem for the present research question focusing on the dimensionality of innovation. In fact, due to the extensive correlation between both variables this does not lead to a missing variable problem. The same reasoning holds for reducing multicollinearity in the multivariate case when performing a PCA and a multicollinearity diagnostic check in order to identify severe correlations and reduce them by selecting representative variables.

For the highly correlated *Social Capital* dimension 'Weak Ties and Social Trust' and the variable EQI we applied a different approach. Charron et al. (2014) illustrate the strong association between quality of governance and social trust in European regions. In his pioneering work on efficiency discrepancies in regional administrations in Italian provinces Putnam et al. (1993) suggests that such differences are due to discrepancies in cultural norms with respect to social interaction and interpersonal trust. Hence, we integrate the component 'Weak Ties and Social Trust' in the model and also the residual effect exerted by institutions by inserting the residual values from a regression of EQI on 'Weak Ties and Social Trust'. Table A.4 in the Appendix describes the independent variables used in the final regression models, and Table A.5 presents the excluded variables with the corresponding reason for exclusion.

4. Results

4.1 Compression of innovation indicators

We process all eight innovation indicators with PCA applying a Varimax-type rotation method. According to the Kaiser criterion, the PCA extracts two independent components with eigenvalues greater than unity with an overall explained variance of 80.2%. Bartlett's Test of Sphericity produces highly significant results and the Kaiser-Meyer-Olkin criterion of sampling adequacy is 0.735, suggesting general suitability for the indicators to be used in PCA. The communalities and the rotated component matrix of the PCA are shown in Table 3.

Table 3
Communalities and loading matrix from principal component analysis on regional innovation indicators

Indicators	Communalities	Components	
		C1	C2
New-to-firm product innovators	.937	.959	.127
Goods innovators	.912	.948	.119
New-to-market product innovators	.909	.943	.136
Process innovators	.823	.860	.290
Service innovators	.649	.791	.152
Patent applications	.575	.691	-.311
Turnover share of new-to-firm product innovations	.837	-.031	.915
Turnover share of new-to-market product innovations	.774	.281	.834
Eigenvalue		4.63	1.78
% of explained variance (cumulative)		57.9	80.2

Notes:

PCA with Varimax rotation. Kaiser-Meyer-Olkin measure of sampling adequacy: 0.5 number of observations: 104. Grey background denotes factor loadings exceeding 0.5 in absolute value.

At first glance the results seem clear: the information compression with PCA satisfies all established statistical quality criteria and suggests that innovation is not unidimensional but consists of two independent dimensions. The two resulting components clearly separate the two levels of innovation output. The first component is characterized by high loadings of all indicators reflecting the generation of innovations, namely the CIS indicators referring to the percentage of firms with the introduction of goods, services, and process innovations as well as both variables describing the degree of novelty of introduced product innovations. In addition, the patent indicator exhibits a high loading on this component. The second component shows high loadings for both variables reflecting the market success of introduced innovations and thus reflects the second level of innovation output. However, the results do not fit established theory without difficulty. Particularly three issues stand out. Firstly, although more than one innovation dimension was expected, a separation of first and second degree of innovation output is surprising, because indicators corresponding to the same causal chain should exhibit high loadings on the same components (as illustrated in Figure 1). However, since an orthogonal factor rotation is applied, component 1 (C1) and component 2 (C2) by definition show no correlation[9]. This means that direct innovation summarized in the first component has no impact on the turnover share from sales of innovative products, which is hardly comprehensible, particularly in the case of innovations new to the market. Time lags between innovation activities and market success of these introduced innovations may indeed be conceivable, complete independence, however, does not seem plausible. Secondly, patent applications show a negative loading on the second component. Even if the absolute value is less than 0.5, it must be

[9] A PCA with an oblique rotation method (e.g. the Oblimin rotation approach) produces qualitatively the same results and shows no significant correlations among the two resulting components. These results are not reported here, but can be made available by the authors upon request.

taken into account. A negative association between patents and the turnover share of newly introduced innovations is in any case counterintuitive. The third emerging issue regards the loading of the patent indicator. This common innovation indicator shows a remarkably low communality of 0.575. Considering that patents are reflected by the first component, a loading of 0.691 implies that less than 50 percent ($0.691^2<0.5$) of the information of this variable is used in the factorization. If the remaining 50 percent are not regarded as statistical noise, this finding suggests the existence of innovation aspects that are exclusively (with regard to the considered output indicators) captured by patents.

The following analysis of the impact of the considered driving forces on the individual innovation output indicators as well as on the two derived indices may shed some additional light on these concerns.

4.2 Determinants of Innovation

The impact of the input variables on regional innovation (both on the innovation indicators as well as on the obtained innovation components) is analysed by regression analysis. A spatial error approach is applied since the residuals resulting from OLS models show significant autocorrelation[10]. Hence, the following model is estimated

$$y = X\beta + u \quad \text{with} \quad u = \rho W u + \varepsilon,$$

where y is the $n \times 1$ vector of values of the dependent variable (n denotes sample size), X the $n \times k$ matrix of the values of the independent variables (k denotes the number of independent variables), β the $k \times 1$ vector of regression coefficients, u the spatially autocorrelated remainder noise, ρ is the spatial correlation coefficient of the noise, W the $n \times n$ spatial weighting matrix (row-standardized Queen matrix), and the ε_is are independently, identically distributed with mean zero and variance σ^2. In order to assess the model fit two statistics are employed (I is the $n \times n$ identity matrix, $\hat{\beta}$ denotes the estimates of the parameter vector β, corr indicates the Pearson correlation coefficient).

$$\mathrm{Pseudo}-R^2 = \mathrm{corr}\left(y, X\hat{\beta}\right)^2, \text{ and}$$

$$\mathrm{Pseudo}-R^2_{\mathrm{spatial}} = \mathrm{corr}\left(y, X\hat{\beta} + (I - \hat{\rho}W)^{-1}\left(y - X\hat{\beta}\right)\right)^2,$$

where the latter captures the spatial autocorrelation. These results of the estimation are shown in Table 5.

[10] We choose a spatial error model because the focus of the present approach is on the determinants of the individual innovation indicators and not on spillovers to adjacent regions.

We first concentrate on the innovation indicator patents, which is profoundly analysed in the literature, in order to obtain insights into the appropriateness of the employed approach (cf. Table 5). The identified impact variables are R&D (measured in the variables private R&D expenditures and government R&D expenditures), quality of institutions (EQI) and agglomeration forces (proxied by the percentage of urban population). All of these variables have a statistically significant positive impact on log patents, being in line with the results reported in the literature (Bottazzi and Peri, 2003; Crescenzi et al., 2013; Greunz, 2004; Moreno et al., 2005; Varsakelis, 2006). Two of the dimensions of *Social Capital* have a statistically significant impact. However, the impact of the component 'Weak Ties and Social Trust' is prominent, indicating that a trustful society combined with the high quality of institutions favours regional innovation in terms of strong patent activity (Akçomak and ter Weel, 2009; Crescenzi et al., 2013; Hauser et al., 2007; Kaasa, 2009). In addition, we observe a statistically significant and negative coefficient of the second *Social Capital* component 'Strong Ties'. This impact is notably lower than the 'Weak Ties and Social Trust' component.

The highly significant spatial correlation coefficient underlines the suitability of the spatial modelling approach (Anselin, 1988; Moreno et al., 2005; Paci and Usai, 1999).

In order to investigate whether the innovation indicators can be compactly summarised in a few appropriate components, e.g. in components C1 and C2, the focus is put on the comparison of the regression results across the innovation indicators as well as the components.

The first striking fact is that, with the exception of the impact of the regional share of manufacturing employees on the turnover share of new-to-firm sales, none of the remaining examined innovation drivers shows a significant impact on either of the innovation sales variables, i.e. the second level of innovation output. In addition, also the corresponding component 2 shows only a significant coefficient for a single variable, the expenditures for R&D efforts in the higher education sector. The *pseudo*-R^2_{spatial} of 0.6 almost completely arises due to spatial correlation of the error terms.

This finding indicates either that the applied approach disregards the actual relevant determinants of the turnover share of innovative products or that the underlying indicators regarding 'new-to-firm sales' and 'new-to-market sales' (and consequently the innovation component C2) are characterized by qualitative or conceptual problems. The following indications point to the latter argument. The stability of these indicators over time is investigated. This is accomplished using the Regional Innovation Scoreboard (Hollanders et al., 2014) database that includes data for four observation years (equivalent to four CIS waves). The Regional Innovation Scoreboard (RIS) uses the CIS variables referring to the turnover shares of innovative products combined to a single indicator in its analyses[11]. The inspection shows that this variable varies extensively over the different observation periods and, thus, over the different CIS waves. For the purpose of comparison the correlation coefficients for patent applications also obtained from the RIS database are displayed in Table 4. Because of the serious problems involved with these two indicators, we will not further interpret the corresponding quantitative results, but instead suggest that further research be conducted with regard to the validity of these innovation indicators.

Table 4

The results of the stability analyses of the innovation indicator 'Turnover share of sales of innovative products' are shown for the period 2004 to 2010 using data from the Regional Innovation Scoreboard. The table displays the Pearson correlation coefficient (*correlation*) of this indicator between the different years and the sample size *n* (number of regions). As benchmark the correlation coefficients of patent applications for the same period and obtained with the same database are shown.

		Turnover share of sales of innovative products				Patent applications (EPO)			
Year	Statistics	2004	2006	2008	2010	2004	2006	2008	2010
2004	*correlation*	1	.124	.379**	,316**	1	.988**	.985**	.969**
2006	*correlation*	.124	1	.634**	.468**	.988**	1	.990**	.973**
2008	*correlation*	.379**	.634**	1	.739**	.985**	.990**	1	.984**
2010	*correlation*	.316**	.468**	.739**	1	.969**	.973**	.984**	1
	N	190	190	190	190	186	186	186	186

Note:

** indicates a significance level of 1%.

Besides the above qualitative problems with the indicators concerning the turnover share of sales of innovative products, the regression results are analysed with regard to whether or not the input variables have the same impact on the remaining innovation indicators so that it would make sense to summarize them in a single component, i.e. C1. The findings in Table 5 reveal a multiplicity of evidence for different impacts and the following empirical evidence is discussed: (1) the comparison between the indicator patents and the composite index C1, (2) the impact of 'Government R&D expenditures', (3) the driving forces for 'goods innovators' and 'process innovators' in comparison to the determinants of C1, and (4) the spatial correlation of the residuals.

The difference between log patents and C1 is evident in three aspects: There is a statistically significant impact of 'Government R&D expenditures' on log patents, but there is no longer evidence of this effect on C1. Surprisingly, the importance of the manufacturing sector has an impact on C1, but not on the patents. This stands in contrast to the common assumption that the agglomeration

[11] Furthermore, the Regional Innovation Scoreboard standardizes all indicators between 0 (region with lowest value) and 1 (region with highest value) for each observation year separately.

forces in manufacturing are conducive to patenting activity (Moreno et al., 2005). The third noticeable difference is found in the impact of urbanisation on patenting activities, but not on C1. This is in line with the fact that patenting occurs at the place where an enterprise is registered and that place is frequently in bigger cities (Breschi, 2008). To sum up, these discrepancies demonstrate that the single indicator patenting represents a quite different aspect of innovation than does C1.

Concerning the impact of public R&D, two very different conclusions can be drawn: Just looking at the composite index C1 no significant impact of public R&D is observed. However, the conclusion that public R&D is of little importance is unjustified when investigating this input variable's impact on innovation in its different facets. Evidence of a positive effect of public R&D on both new-to-market innovations and log patents is found. The resulting interpretation for the single indicators is completely different than for the composite index C1.

When comparing the estimates of the innovative inputs on the indicators 'goods innovators' and 'process innovators,' the differences in the impacts are obvious. However, both indicators load strongly on the composite index C1, and their respective communalities are appropriate. The regression results demonstrate that aggregating the innovation indicators to a composite index produces different conclusions regarding the driving forces for innovation output and therefore different policy strategies. The question whether innovation should be measured as a multidimensional concept and investigated using various indicators or whether innovation should be simplified to a one-dimensional concept is clearly answered in favour of a multidimensional problem with various recommendations for the dimensions of innovations captured in the indicators. To this effect our results indicate that any kind of innovation ranking is of very limited use.

In regional analyses spatial effects are of primary importance. The strength of spatial effects is shown by the spatial correlation coefficient. Even if all spatial correlation coefficients have the same sign, we find relevant differences in their sizes. In fact, the spatial correlation coefficient of patenting is the smallest and the estimate for process innovation is the largest. At first glance it seems that spatial spillover effects are much stronger for process innovations than for patenting activities.

The aim of the paper was not to comprehensively model innovation production, but to demonstrate the inappropriateness of a composite index for measuring innovation due to various driving forces of the innovation indicators. Different impact structures on the different innovation output indicators are identified. Therefore, focusing only on a composite index as well as only on a single indicator may cause a not negligible loss of information.

Table 5

Estimation results from spatial error regression models (all displayed coefficients are standardized coefficients). The individual innovation output indicators as well as the regional component scores resulting from the PCA are employed as dependent variables, the patent indicator is included as a log-patent in order to account for the skewed distribution of this variable.

	goods	service	process	new-to-market	new-to-firm	new-to-firm sales	new-to-market sales	log(patent)	C1	C2
Private R&D expenditures	.103	.169*	.091	.209**	.148*	.020	-.059	.152***	.229***	-.136
Government R&D expenditures	.102	.020	.153	.190*	.138	.048	.096	.111*	.126	.059
Higher education R&D expenditures	.026	.139	.046	.052	.144	.174	.101	-.045	.032	.185*
Strong Ties	-.069	-.096	-.216**	-.005	-.018	.189	-.011	-.086*	-.122	.077
Weak Ties and Social Trust	.440***	.101	.301*	.316**	.313**	.023	.233	.564***	.329***	.121
Political Interest	-.00	-.109	.026	.009	-.074	-.083	.194	-.011	.001	.088
Traditional vs. Secular-rational Values	-.089	-.300**	-.118	-.069	-.207*	.042	.058	-.069	-.147	.051
EQI residuals	.410***	.082	.269**	.319***	.338***	-.023	.043	.296***	.308***	-.019
Employment manufacturing	.357***	.002	.189*	.307***	.266**	.238*	.172	.059	.218**	.206
Urban population	-.003	.126	-.027	.046	.006	-.035	-.018	.130**	.045	-.050
Spatial correlation coefficient	.559***	.661***	.71***	.506***	.604***	.632***	.702***	.488***	.66***	.732***
Pseudo-R^2	.58	.47	.39	.60	.58	.26	.09	.88	.66	.24
Pseudo-R^2_{spatial}	.70	.66	.70	.69	.72	.49	.53	.90	.80	.60
Observations	104	104	104	104	104	104	104	104	104	104

Notes:
*p<0.05; **p<0.01; ***p<0.001; C1 and C2 denote the two components resulting from principal component analysis on innovation output indicators.

5. Discussion and Conclusion

We started with the idea that reducing innovation to only one composite index is not justified because of the multidimensionality of innovation. This hypothesis was only partly corroborated. Although two clearly interpretable orthogonal components are obtained using principal component analysis (PCA), the component representing the sales variables (‘Turnover share of new-to-firm product innovations’ and ‘Turnover share of new-to-market product innovations’) is neither influenced by any innovative input variable nor stable in time. This gave rise to the conclusion that these indicators need to be profoundly examined before application can be considered. Although they theoretically provide the most rigorous information on pure innovation (i.e. commercially successful new products), their empirical associations, over time and with the innovation variables, conflict with traditional conceptions of innovation processes. Consequently, their adoption as single indicators or in composite indices requires a refined understanding of these indicators in terms of validity and reliability. Such research regarding the quality of CIS data could be simplified if the original micro data were accessible through Eurostat including the regional affiliation of each firm.

The second finding is probably of broader interest: The PCA identifies a component, summarizing all innovation output indicators (except the sale variables). The respective statistics indicate that the factorization is admissible and that this component is a good representative of the respective set of indicators. Looking at the result from a theoretical instead of a statistical point of view, the fact that only 50% of the information content of the patenting indicator is used in the relevant component is not satisfying at all. What about the remaining 50%? Are they of no relevance? It seems much more probable that the unexplained 50% represents an aspect of innovation not captured by the other indicators and therefore not included. But precisely the finding that an aspect is not captured by other indicators makes this indicator of special interest.

However, even if the communalities of innovation indicators are high and therefore statistically the indicators’ information is appropriately captured in the composite index, the impact of the input variables on the single indicators is quite different from the respective impact of the input variables on the composite index. Therefore, quite different conclusions (different recommendations for regional policy strategies) are drawn depending on whether innovation is regarded as a multidimensional concept with various facets or merely as a one-dimensional index.

The necessity to analyse the investigation of the original indicators of innovation together with the component is confirmed by our analyses. The various driving forces indicate various strategies in political interest. It is obvious that reducing a complex phenomenon to only one composite index, thus allowing impressive rankings, is very attractive. However, the obtained results suggest that reducing information in a too early stage of scientific research may obscure the most interesting results and even give rise to partially wrong political suggestions.

Our investigation involving about 100 regions can give only a preliminary indication, but further investigation of this problem appears worthwhile as rankings become more and more popular and important political decisions rely on them.

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Appendix

Table A.1

CIS indicator construction (firm level)

Indicator name	Section[a]	Question	Codification
Goods innovators	2.1	During the three years 2006 to 2008 did you introduce: new or significantly improved goods?	Yes: 1 No: 0
Services innovators	2.1	During the three years 2006 to 2008 did you introduce: new or significantly improved services?	Yes: 1 No: 0
Process innovators	3.1	During the three years 2006 to 2008 did you introduce (min. 1): new or significantly improved methods of manufacturing or producing goods or services; new or significantly improved logistics, delivery or distribution methods for inputs, goods, or services; new or significantly improved supporting activities for processes, such as maintenance systems or operations for purchasing, accounting, or computing?[d]	Yes: 1 No: 0
New-to-firm innovators	2.3	Were any of your product innovations (goods or services) during the three years 2006 to 2008: only new to the firm?[b]	Yes: 1 No: 0
New-to-market innovators	2.3	Were any of your product innovations (goods or services) during the three years 2006 to 2008: new to your market?[c]	Yes: 1 No: 0
Turnover share of new-to-firm innovations	2.3	Turnover share in 2008 of goods or services innovations introduced from 2006 to 2008 that were only new to the firm.	Share
Turnover share of new-to-market innovations	2.3	Turnover share in 2008 of goods or services innovations introduced from 2006 to 2008 that were new to the market.	Share

Notes:

[a] Refers to the section number of the relevant question in the CIS2008 Eurostat-harmonized questionnaire.

[b] The firm introduced a new or significantly improved good or service that was already available on the market from competitors.

[c] The introduced good or service may have already been available on other markets.

[d] The CIS in the United Kingdom includes only a single question asking whether process innovations were introduced in the observation period under consideration or not.

Table A.2

EVS 2008 variables included in principal component analysis (PCA) for *Social Capital* dimensions following Hauser et al. (2007) and Bjørnskov (2006).

Dimension	EVS Variable
Strong Ties	How important in your life is: family? How important in your life are: friends? How important in your life is: politics?
Weak Ties and Social Trust	Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with people? List of groups of people with an indication of which ones one does not want to have as neighbours (sum over all groups, generated variable) List of groups indicating the one in which you hold membership (sum of group memberships, generated variable) List of groups with volunteer activity (sum of groups with volunteer activity, generated variable)
Political Interest	How often do you discuss political matters with your friends?

Communalities and loading matrix from principal component analysis on social capital variables

Variables	Communalities	Components		
		1	2	
How important in your life: friends?	.978	0.969	-0.054	-0.188
How important in your life: family?	.982	0.965	-0.104	0.040
Sum of groups in which you hold membership	.917	0.956	-0.223	-0.135
Sum of groups for which you do volunteer work	.743	-0.179	0.911	0.235
Generalized trust	.705	0.228	0.809	0.191
Sum of groups of people that you do not want to have as neighbours	.736	-0.350	0.763	0.017
How often do you discuss political matters with your friends?	.880	-0.343	0.671	-0.410
How important in your life: politics?	.943	-0.216	0.186	0.894
Eigenvalue		3.16	2.61	1.11
% of explained variance (cumulative)		0.39	0.72	0.86

Notes:

PCA with Varimax rotation. Kaiser-Meyer-Olkin measure of sampling adequacy: 0.657. Grey background denotes component loadings exceeding 0.5 in absolute value.

Table A.3

Variables based on EVS2008 included in principal component analysis (PCA) for *Culture* dimensions following Inglehart and Baker (2000) and Inglehart and Welzel (2010).

Dimension	Variables
Traditional vs. Secular-rational Values	Importance of God Obedience and faith vs. independence and determination: (List of qualities that children can be encouraged to learn at home) Disapproval of abortion National pride
Survival vs. Self-Expression Values	Priority for economic and physical security Feeling of unhappiness Disapproval of homosexuality Abstaining from signing petitions

Communalities and loading matrix from principal component analysis on cultural variables

Variables	Communalities	Components	
		1	2
Importance of God	.858	.868	.323
Children Obedience Faith	.726	.840	.142
Justification Abortion	.727	.810	.268
National Pride	.486	.684	.137
Feeling Happiness	.680	.092	.856
Economic Physical Security	.740	.145	.812
Disapproval Homosexuality	.860	.502	.779
Never Sign Petition	.715	.358	.766
Eigenvalue		2.99	2.80
% of explained variance (cumulative)		0.37	0.72

Notes:

PCA with Varimax rotation. Kaiser-Meyer-Olkin measure of sampling adequacy: 0.737. Grey background denotes component loadings exceeding 0.5 in absolute value.

Table A.4

Independent variables used in the final regression models

Group	Indicator	Description and calculation	Source
Research and development	Private sector R&D expenditures	Average yearly expenditures for R&D efforts in the business enterprise sector from 2006 to 2008 (million euros in ppp per inhabitant)	Eurostat
	Government sector R&D expenditures	Average yearly expenditures for R&D efforts in the government sector from 2006 to 2008 (million euros in ppp per inhabitant)	Eurostat
	Higher education sector R&D expenditures	Average yearly expenditures for R&D efforts in the higher education sector from 2006 to 2008 (million euros in ppp per inhabitant)	Eurostat
Social capital	Strong Ties	Relationships with family and friends (resulting from PCA on eight regionally aggregated variables)	EVS2008; own calculation
	Weak Ties and Social Trust	Association activity and confidence in other humans (resulting from PCA on eight regionally aggregated variables)	EVS2008; own calculation
	Interest in Politics	Engagement with society (resulting from PCA on eight regionally aggregated variables)	EVS2008; own calculation
Culture	Traditional vs. Secular-rational Values	Resulting from PCA on eight regionally aggregated EVS variables	EVS2008, own calculation
Quality of governance	EQI residuals	Residuals from the regression of EQI (European Quality of Government Index) on *Social Capital* dimension 'Weak Ties and Social Trust'	Charron et al. (2014); own calculation
Economic structure	Employment manufacturing	Manufacturing employment as share of total employment (average 2006 to 2008)	Eurostat
	Population in urban areas	Share of population living in NUTS 3 regions classified as urban areas (in 2008)[a]	Eurostat

Notes:
[a] Calculation of this indicator is based on the European Union urban-rural typology. This typology classifies regions as 'predominantly rural,' 'intermediate' or 'predominantly urban' (Eurostat, 2010).

Table A.5

Variables excluded either by the PCA computed in the first step or based on the multicollinearity diagnosis for the regression models in the second step.

Group	Variable	Description and calculation	Source	Reason for exclusion
Research and development	Private sector R&D personnel	Average share of R&D personnel in the business enterprise sector as a share of total population from 2006 to 2008	Eurostat	Step 1: Three uncorrelated PCA components are obtained and for each component a representative variable is employed (cf. Table A.4).
	Government sector R&D personnel	Average share of R&D personnel in the government sector as a share of total population from 2006 to 2008	Eurostat	
	Higher education sector R&D personnel	Average share of R&D personnel in the higher education sector as a share of total population from 2006 to 2008	Eurostat	
	Private sector researchers	Average share of researchers in the business enterprise sector as a share of total population from 2006 to 2008	Eurostat	
	Government sector researchers	Average share of researchers in the government sector as a share of total population from 2006 to 2008	Eurostat	
	Higher education sector researchers	Average share of researchers in the higher education sector as a share of total population from 2006 to 2008	Eurostat	
Human capital	Tertiary education	Share of population with tertiary education	Eurostat	Step 1: A PCA component is identified. Therefore, only one variable, e.g. tertiary education, is used. Step 2: Tertiary education is also dropped according to the high correlation with employment manufacturing.
	HRST	Persons with tertiary education (ISCED) and/or employed in science and technology (as share of total population)	Eurostat	
	HRST-O	Persons employed in science and technology (as share of total population)	Eurostat	
	HRST-E	Persons with tertiary education (ISCED) (as share of total population)	Eurostat	
	HRST-C	Persons with tertiary education (ISCED) and employed in science and technology (as share of total population)	Eurostat	
Culture	Survival vs. Self-Expression Values	Resulting from PCA on eight regionally aggregated EVS variables	EVS2008; own calculation	Step 2: Due to the high correlation with EQI this component is excluded from further analysis.

Quality of governance	Trust in national institutions	Resulting from PCA applied to seven EVS variables	EVS2008; own calculation	Step 1: A PCA component is identified therefore EQI as representative variable is employed further.
	Trust in international institutions	Resulting from PCA applied to seven EVS variables	EVS2008; own calculation	
Economic structure	GDP per capita	Gross domestic product per capita (in million euros in ppp; average 2006 to 2008)	Eurostat	Step 1: A single PCA component is obtained. Due to the high correlation of GDP per capita with R&D expenditures, the high correlation of employment services with HRSTO and the high correlation of employment KIS with tertiary education the remaining two variables are used in the regression analysis. Both are used as the communalities are not that high and to keep as much information as possible of 'economic structure'.
	Employment services	Employment in service industries as share of total employment (average 2006 to 2008)	Eurostat	
	Employment KIS	Employment in knowledge-intensive services as share of total employment (average 2006 to 2008)[a]	Eurostat	

Notes: [a] According to Eurostat, the following NACE Rev. 2 divisions are classified as knowledge-intensive services (KIS): 50, 51, 58 to 63, 64 to 66, 69 to 75, 78, 80, 84 to 93.

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Matthias Siller, Christoph Hauser, Janette Walde, Gottfried Tappeiner

Measuring regional innovation in one dimension: More lost than gained?

Abstract
In both academic literature and political discussions the concept of innovation is recognized as an essential ingredient in economic development and competitiveness for firms, regions, and nations. Innovation also ranks at the top of policy agendas in the field of regional policy. Therefore, the attractiveness of an appropriate innovation index for ranking regions and further developing them along a more or less objective measurement scale is evident. However, whether such rankings help convey a better understanding of innovation and its drivers, or whether they are merely a special type of 'beauty contest' with little substance is the focus of our analyses. To deny the latter, the innovation output indicators used for the composite index have to be appropriate representatives of the underlying innovation concept and each indicator has to be driven by the same impact factors. If this is not the case, interpretation of the index inevitably gives rise to partly inappropriate policy recommendations. In order to demonstrate this claim we elaborate a set of innovation indicators at the regional level based on the theoretical concept of the OECD document 'The Measurement of Scientific and Technological Activities, Proposed Guidelines for Collecting and Interpreting Technological Innovation Data' known as the 'Oslo Manual' (OECD, 2005) and their empirical implementation in the Community Innovation Survey. Additionally, innovation drivers well established in the literature are collected to estimate their impact on each innovation indicator as well as on the composite index derived from the innovation indicators. The question whether innovation should be measured as a multidimensional concept and investigated using various indicators or whether simplifying innovation to a one-dimensional concept is appropriate is clearly answered in favor of the multidimensional approach. Surprisingly, this is not due to the multidimensionality of the indicators themselves (all statistical measures indicate that the considered variables are sufficiently represented by one component), but to our first evidence that the innovation output indicators are driven by various impact factors and can therefore be influenced by various political strategies. According to these findings any type of innovation ranking is of very limited use.

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