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# Rethinking regional performance: examining the role of economic growth and industrial clusters in the objective well-being of European regions

Nils Grashof<sup>1</sup> 

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**Abstract** While promoting the well-being of people is the ultimate goal of all EU social and economic policies, research in this area has been mainly limited to income-based measures of well-being, such as GDP per capita, especially at the regional level. Therefore, this study aims to go beyond income-based measures and examine the spatial distribution and drivers of objective well-being in European regions. To achieve this, a unique panel dataset is created by integrating regional data on objective well-being (based on the EU-Social Progress Index), economic growth, industrial clusters and knowledge structure, covering 165 NUTS-2 regions from 11 EU countries (between 2011 and 2018). Based on dynamic panel regressions using a system generalized method of moments (GMM) approach, it is shown that the economic growth promotes the objective well-being in regions. Evidence is also found that the industrial structure within regions is an additional driver. Regions with a diverse industrial cluster portfolio are more likely to have high objective well-being. However, this influence is negatively moderated by the strength of the industrial clusters, which possibly refers to size-related negative externalities. Besides the economic effects, industrial cluster structures can therefore also influence the objective well-being in regions. To promote regional well-being, regional policies should support a diverse industrial cluster portfolio rather than a regional cluster structure that is overly specialized in relatively few large industries.

**Keywords** Well-being · Objective well-being · GDP · Clusters · Agglomeration · European regions

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**Zusammenfassung** Obwohl die Förderung des Wohlstands der Menschen das oberste Ziel aller sozial- und wirtschaftspolitischen Maßnahmen der EU ist, beschränkte sich die Forschung in diesem Bereich bisher hauptsächlich auf einkommensbasierte Maße des Wohlstands, wie das BIP pro Kopf, insbesondere auf regionaler Ebene. Daher zielt diese Studie darauf ab, über einkommensbasierte Messgrößen hinauszugehen und die räumliche Verteilung und die Triebkräfte des objektiven Wohlstands in europäischen Regionen zu untersuchen. Hierzu wird ein Paneldatensatz erstellt, der regionale Daten zum objektiven Wohlstand (basierend auf dem EU-Index für sozialen Fortschritt), zum Wirtschaftswachstum, zu Industrieclustern und zur Wissensstruktur enthält und 165 NUTS-2-Regionen aus 11 EU-Ländern (zwischen 2011 und 2018) abdeckt. Auf der Grundlage dynamischer Panel-Regressionen unter Verwendung einer verallgemeinerten Momentenmethode (GMM) wird gezeigt, dass das Wirtschaftswachstum den objektiven Wohlstand in Regionen fördert. Es wird auch nachgewiesen, dass die Industriestruktur innerhalb der Regionen ein zusätzlicher Einflussfaktor ist. Regionen mit einem breit gefächerten Portfolio von Industrieclustern haben eine höhere Wahrscheinlichkeit für ein hohes objektives Wohlergehen. Dieser Einfluss wird jedoch durch die Stärke der Industriecluster abgeschwächt, was möglicherweise auf größenbedingte negative Externalitäten zurückzuführen ist. Neben den wirtschaftlichen Effekten können industrielle Clusterstrukturen also auch das objektive Wohlergehen in Regionen beeinflussen. Um das regionale Wohlergehen zu fördern, sollte die Regionalpolitik ein vielfältiges Portfolio von Industrieclustern unterstützen und nicht eine regionale Clusterstruktur, die übermäßig auf relativ wenige große Industrien spezialisiert ist.

## 1 Introduction

The ultimate goal of economics is to understand and improve social welfare.<sup>1</sup> In the analysis of the underlying mechanisms and drivers of social welfare, most researchers, however, tend to narrow down their focus to income-based measures of well-being, such as GDP per capita, and related purely economic measures, such as productivity and employment (Castellacci 2023; Hartmann and Pyka 2013). Linked to the “beyond GDP” initiative (e.g. Fleurbaey 2009; Stiglitz et al. 2009) research has therefore started to widen its well-being understanding towards non-economic measures, such as environmental and/or health-related outcomes. Despite some important exceptions (e.g. Peiró-Palomino et al. 2020), these analyses are, however, primarily conducted on the national level. Given the shown interregional divergences in economic terms (Iammarino et al. 2019), such a common neglect of non-economic effects at the regional level seems quite surprising and also insufficient (Tomaney 2017). This is particularly true in the light of the “beyond GDP” initiative, which criticises an overly narrow understanding of social welfare (e.g. Fleurbaey 2009). Even the creator of the GDP, Nobel Prize winner Simon Kuznets, warned that “[t]he

<sup>1</sup> In line with previous research (e.g. Binder and Witt 2011), social welfare and well-being are used interchangeably here.

welfare of a nation can, therefore, scarcely be inferred from a measurement of national income as defined above.” (Kuznets 1934, p. 7).

This study therefore wants to move beyond income-based measures and investigate the spatial distribution as well as drivers of objective well-being in European regions. Building on Amartya Sen’s capabilities approach from 1985, which stresses the importance of ends (e.g. decent standard of living) over means (e.g. income per capita), and the framework of the EU Regional Social Progress Index (SPI), the objective well-being is measured at the NUTS-2 level for the period between 2011 and 2018. Unlike other objective well-being indexes, such as the Human Development Index (HDI), the SPI excludes GDP or other income-based indicators and consequently does not get distorted by them. It therefore adequately captures social advancements and allows to be decoupled from the regional economic growth (Annoni et al. 2016; Fehder et al. 2018). Following the discussion and evidence about the Easterlin Paradox on the national level (e.g. Easterlin 1974; Stevenson and Wolfers 2013) particular the relationship between GDP and well-being is of interest in this context.

As another possible driver of regional differences in objective well-being, this study is also interested in the industrial structures in regions. The geographic concentration of related economic activities is a fundamental part of today’s economic reality (Delgado et al. 2014; Nathan and Overman 2013). As such, industrial clusters and their potential effects have fascinated researchers and policy makers alike (Martin and Sunley 2003; Sedita et al. 2012). Despite this popularity, however, the focus has so far been primarily on the economic effects of clusters as measured by traditional economic indicators such as productivity (e.g. Knobon et al. 2016), innovativeness (e.g. Boix and Galletto 2009) or employment growth (e.g. Delgado et al. 2014; Porter 2003). Broader socioeconomic influences that could be negatively affected by diseconomies of agglomeration have been largely overlooked (Grashof and Fornahl 2021; McCann and Folta 2008), although some exceptions have found an influence on regional inequality (e.g., Kwon and Sorenson 2023, Guo et al. 2020) and rising housing prices (e.g., Prevezer 1997). It therefore remains unclear whether the frequently observed and politically supported co-location of firms from related industries actually promotes the social welfare in the respective regions (Rocha et al. 2020). Already drawn conclusions about the effects of clusters might therefore not tell the whole story, but eventually only the bright side of clusters.

The corresponding empirical analyses rely on various data sources. For the determination of the objective well-being in regions, the already described multidimensional framework of the EU Regional Social Progress Index (SPI) is used. The SPI is based on the three dimensions (Basic Human Needs, i.e. the ability of a region to meet the basic human needs of its citizens; Foundations of well-being, i.e. building blocks that enable citizens to improve and maintain their quality of life; Opportunities, i.e. opportunities for all individuals to reach their full potential), which can be further divided into four components, which are then further composed of two to five indicators collected from different databases, such as the European Social Survey (Annoni et al. 2016; Fehder et al. 2018). Moreover, in line with previous studies (e.g. Ketels and Protsiv 2016, 2021), the number of different industrial clusters and the strength of these industrial cluster structures (capturing the absolute size

and productivity) in European regions are identified based on information provided by the European Cluster Observatory. By further enriching this dataset with patent data from the OECD Regpat database and regional data from Eurostat, a unique panel dataset is created covering 165 NUTS-2 regions from 11 EU countries for the period between 2011 and 2018. Based on dynamic panel regressions using a system generalized method of moments (GMM) approach (Blundell and Bond 1998), it is shown that economic growth<sup>2</sup> enhances the objective well-being in regions. Moreover, while a diverse industrial structure (i.e. broad portfolio of different industrial clusters) is generally a driver of the objective well-being in regions, its positive influence is negatively moderated by the strength of industrial clusters, possibly indicating size-related negative externalities.

By quantitatively investigating the spatial distribution and drivers of objective well-being in European regions, this article extends previous research in the field of regional and innovation studies towards a more comprehensive understanding of regional performance (i.e. objective well-being at the regional level) and the importance of economic growth and industrial structure in regions in this context. As such, this paper also offers a pragmatic value, in particular for the further development of current regional policy approaches.

The remainder of this paper is structured as follows: In the next section, the theoretical background on well-being, economic growth and industrial clusters are introduced, thereby deriving the underlying hypotheses of this paper. In the third section, the data sources, the corresponding variables and the methodological approach are outlined. The subsequent section presents and discusses the descriptive and econometric results. A final section concludes the paper and provides some promising future research endeavours.

## 2 Theoretical background: well-being, economic growth and industrial clusters

### 2.1 Understanding well-being

Defining well-being has been a challenging task given its complexity and multidimensionality (D'Urso et al. 2020; Voukelatou et al. 2021). Most commonly, well-being has been equated with economic welfare, and thus GDP has been the standard measure of well-being (D'Urso et al. 2020). Nevertheless, its dominant and exclusive use as a measure of well-being has been increasingly criticized as too narrow and flawed, since it ignores non-economic impacts (Fehder et al. 2018; Jones and Klenow 2016). As a result, initiatives have been launched to create measures that go “beyond GDP” (e.g. Fleurbaey 2009; Stiglitz et al. 2009).<sup>3</sup> However, most of these have taken place at the national level, ignoring potential regional differences. With important exceptions (e.g. D'Urso et al. 2020; Lenzi and Perucca 2020; Peiró-

<sup>2</sup> In line with previous studies (e.g. Fagerberg and Srholec 2008), when referring to economic growth, we refer to its level as measured by GDP per capita (see Section 3.2).

<sup>3</sup> For a summary of various measures, see Domínguez-Torreiro (2016).

Palomino et al. 2020), there have been relatively few attempts to develop indicators at the regional level (Tomaney 2017), which is one of the main motivations for this study.

In general, well-being can be separated into subjective and objective well-being (Binder 2014; D'Acci 2011; Castellacci 2023). The prior approach is rooted in a utilitarian framework, employing life satisfaction and happiness metrics to assess individuals' perceived (subjective) well-being or happiness (McGillivray 2007).<sup>4</sup> Conversely, objective well-being is recognized as a multifaceted notion, centering on tangible and measurable aspects, such as those related to health and education. These factors are instrumental in allowing individuals to perform essential life activities, thus offering them the chance to realize their utmost potential in life (Alkire 2016; Anand et al. 2005; D'Acci 2011). Although both approaches have their advantages and disadvantages (Binder 2014; Binder and Witt 2011), objective well-being is considered most appropriate for the specific research focus of this paper because it comprehensively and objectively captures the facets of a fulfilled life, avoiding the underestimation of deprivation due to hedonic adaptation, as is the case with subjective well-being (Binder 2014; Sen 1987).

The foundational principles of objective well-being are deeply rooted in Amartya Sen's "capabilities approach" (Sen 1985a, b, 1987). With his approach he emphasized the significance of ends, such as a decent living standard, over the means to achieve them, like income per capita (Sen 1987). Central to his approach are the concepts of "capabilities" and "functionings". Functionings describe the various life activities and experiences that individuals' value, ranging from basic necessities such as safety, nutrition, and literacy to more complex accomplishments like engaging in community life. These functions all have intrinsic value and cannot be reduced to each other, making the approach multidimensional. Capabilities, on the other hand, are the possible opportunities individuals have to realize different functionings, hence achieving well-being (Alkire 2016; Anand et al. 2005; Binder 2014). Sen (1992) defines them as follows: "(...) the various combinations of functionings (beings and doings) that the person can achieve. Capability is, thus, a set of vectors of functionings, reflecting the person's freedom to lead one type of life or another. (...) to choose from possible livings." (Sen 1992, p. 40). The capabilities approach, thus, goes beyond individual assessments, as in the case of subjective well-being, and conceives of welfare as a set of objective functionings in life that people are capable of achieving (Binder 2014; Binder and Witt 2011; Sen 1985b).

## 2.2 Economic growth and objective well-being in regions

Although economic growth is often used to explain the assumed positive influence of innovation on well-being (Binder and Witt 2011; Dolan and Metcalfe 2012), the (empirical) link between economic growth and objective well-being is not as well-established as this common assumption suggests—especially at the regional level (e.g. Tomaney 2017). This may be because many measures of objective well-being, such as the HDI, include GDP as a variable for economic growth, preventing

<sup>4</sup> These metrics capture affective, cognitive or both aspects of subjective well-being (Binder 2013).

a meaningful empirical analysis of this relationship.<sup>5</sup> Data limitations have also meant that few studies at the regional level have actually developed a composite indicator of objective well-being (D'Urso et al. 2020; Peiró-Palomino et al. 2020).

Nevertheless, based on previous studies on the national level, it is reasonable to assume that income levels have significant consequences for objective well-being. For instance, economic growth has been shown to be positively associated with employment opportunities (e.g. Sawtelle 2007), to provide the potential for improved population health (e.g. Lange and Vollmer 2017) and to enhance social safety (e.g. Lee and Chang 2006). All of this has a positive influence on objective well-being. Moreover, in general, a higher level of economic wealth, also provides (on average) more consumption opportunities so that material needs can be more easily satisfied (Ranis et al. 2000). However, this to some extent ignores the unequal distribution of economic wealth and the strong empirical evidence that rising income does not necessarily lead to higher well-being, at least in terms of subjective well-being which is known as the Easterlin paradox (Castellacci 2023; Easterlin 1974; Mikucka et al. 2017). Recently, Lenzi and Perucca (2020) have also found evidence for an inverted U-shaped relationship between GDP per capita and subjective well-being at the regional level. While this could potentially also be the case for objective well-being, based on the previous literature review, it is rather assumed that high levels of GDP per capita are associated with overall high levels of objective well-being, which is consistent with recent findings at the national level (e.g. Fehder et al. 2019; Peiró-Palomino et al. 2023). Thus, the following hypothesis is proposed:

**Hypothesis 1** The regional economic growth has a positive influence on regional objective well-being.

### 2.3 Industrial clusters and objective well-being in regions

The corresponding industrial structure within regions is another potential driver of objective well-being in regions. In particular, the geographical agglomeration of related industrial activities, or in other words industrial clusters, has been a central topic from various disciplines in this context (Delgado et al. 2014; Sedita et al. 2012). In general, the sources of agglomeration economies can refer to localization (Marshall 1920) and/or urbanization externalities (Jacobs 1969), which can be further differentiated into related and unrelated variety (Frenken et al. 2007). In the case of industrial clusters, the focus is primarily on localization externalities, which refer to improved access to specialized labor, inputs, knowledge spillovers, and increased demand (Grashof and Fornahl 2021; Lazzeretti et al. 2014; McCann and Folta 2008). However, many clusters also consist of a set of related industries, e.g. buyer-supplier linkages (Frenken et al. 2015; Porter 1998), which is why related variety also matters in this context (Delgado et al. 2016; Kosfeld and Mitze 2023).

Although far from being conclusive (e.g. Grashof 2020), due to their externalities, regional cluster structures have been shown to be associated with increases in productivity (e.g. Ketels and Protsiv 2021), innovation (e.g. Boix and Galletto

<sup>5</sup> For a comprehensive overview of the limits of HDI, see Bilbao-Ubillos (2013).



2009), employment and wages (e.g. Delgado et al. 2014; Porter 2003). This, in turn, has led to increased political interest in and support for regional clusters (Grashof 2021; Zenker et al. 2019). However, broader socioeconomic influences remain so far rather unclear (Rocha et al. 2020), despite some important exceptions that point to potential diseconomies of agglomeration, such as rising housing costs (e.g. Kwon and Sorenson 2023, Guo et al. 2020).

Nevertheless, in regions characterized by a broad portfolio of different clusters, it is reasonable to assume that the positive influences on objective well-being outweigh the negative ones. For example, previous research has been shown that regions with a diverse but cognitively related industry structure also experience higher economic growth (Boschma and Frenken 2011; Content and Frenken 2016; Frenken et al. 2007). Therefore, if Hypothesis 1 is valid, it is likely that a higher number of different industrial clusters will also contribute to higher objective well-being in regions. This also reflects the balanced growth strategy advocated by some development economists (e.g., Nurkse 1953), which suggests that simultaneous and coordinated investment across multiple sectors of the economy is conducive to economic growth.

Beyond this indirect positive influence through economic growth, such a diverse industrial structure also broadens occupational and consumption choices within regions, which has additional positive implications for objective well-being. Since more choices also mean more possible functionings and capabilities as well as higher preference satisfaction, a diverse industrial cluster landscape is likely to increase the objective well-being in regions (Ali and Cantner 2020; Clark 2005; Hartmann and Pyka 2013). Moreover, this diverse industrial landscape also makes regions more resilient to external shocks, such as price fluctuations (Ali and Cantner 2020; Frenken et al. 2007; Staber 2001), which may otherwise have negatively affected the object well-being in regions.

In addition to the previous arguments, industrial clusters also offer some structural characteristics that can potentially improve the objective well-being of regions. In general, clusters are commonly characterized by strong regional ties (Glasmeier 1991; Giuliani 2007) and strong (formal and informal) institutional backgrounds (Becattini 1990; Molina-Morales 2005). Both characteristics also contribute to the social cohesion in regional clusters (Rocha et al. 2020). In turn, such social cohesion, or more broadly the social capital of regions, has been shown to be positively associated with subjective well-being (Puntscher et al. 2015). It is therefore conceivable that industrial clusters provide social and institutional structures that are also conducive to objective well-being.

Taken together, a diverse industrial cluster landscape is likely to increase objective well-being within regions through (i.) an indirect influence of economic growth, (ii.) a broadening of occupational and consumption choices, (iii.) a strengthening of regional resilience to external shocks, and (iv.) supportive social and institutional structures. Thus, the following hypothesis is proposed:

**Hypothesis 2** Regions with a high number of different industrial clusters (i.e. a diverse cluster portfolio) are more likely to have high objective well-being.

Nevertheless, not all industrial clusters are also alike. Instead, the effects of industrial clusters have been shown to vary according to their composition (Delgado et al.



2014; Grashof 2020; McCann and Folta 2011). The strength, for example in terms of size and/or productivity, of the related industries that constitute an industrial cluster is one dimension that is often examined in this context (e.g. Delgado et al. 2016; Ketels and Protsiv 2021). In terms of economic performance, a positive relationship has been observed with the strength of industrial clusters. For example, Wennberg and Lindqvist (2010) find evidence of a positive influence of cluster strength on firm survival, job creation, VAT and wage payments for new entrepreneurial firms in Sweden. Moreover, Slaper et al. (2018) show that traded cluster strength is positively related to productivity growth and compensation per employee growth in US metropolitan statistical areas. These findings are also consistent with the unbalanced growth approach (e.g. Hirschman 1958; Perroux 1955), which, in contrast to the balanced growth approach, advocates concentrating investment in a few key industries with growth potential to support economic growth.

Despite these rather positive results in terms of economic impact, overly strong and specialized industrial cluster structures can also have negative effects. For example, since strong industrial clusters are primarily characterized by their pronounced size and productivity (Ketels and Protsiv 2016), size-based negative externalities may arise, leading to what are sometimes called congestion costs (McCann and Folta 2008; Prevezer 1997). These costs include among other things increased traffic, housing costs and crimes (Saito and Wu 2016), negatively affecting the overall objective well-being. Rising costs and environmental degradation are two vivid examples in this context. The higher regional density of firms leads to increased competition for labor, land, and other inputs, resulting in rising prices for these inputs. This in turn leads to an overall higher cost of living, not only in terms of housing prices (e.g., in San Francisco, housing prices have quadrupled in 30 years), but also in terms of prices at restaurants and supermarkets, which not everyone can afford (Kwon and Sorenson 2023; McCann and Folta 2008). In addition, the increasing regional density of firms also has implications for pollution. Although the evidence is not yet conclusive<sup>6</sup> (Chen et al. 2018), most recent studies emphasize that excessive industrial clustering increases environmental pollution in regions (e.g. Hao et al. 2022; Yu et al. 2022), which may also negatively affect regional health (Azimi and Rahman 2024). Moreover, if the industrial employment and productivity structure within regions is concentrated in a small number of strong industrial clusters, external shocks that negatively affect the objective well-being may not be absorbed as well as in regions with a more diversified industrial structure (see Hypothesis 2).

Consequently, there are reasonable arguments for both directions of influence. However, it is assumed that through its positive influence on economic performance, strong industrial cluster structures are in total rather conducive for the objective well-being in regions. Thus, the following hypothesis is proposed:

**Hypothesis 3** Regions with strong industrial clusters are more likely to have high objective well-being.

<sup>6</sup> Some studies have also found that industrial agglomeration can lead to a reduction in emissions due to economic scale effects and knowledge spillovers. For a good overview, please see Chen et al. (2018).

### 3 Data, variables, and econometric strategy

To empirically test these hypotheses, the following section presents the underlying data sources, the main variables of objective well-being, economic growth, regional clusters, as well as the corresponding econometric approach.

#### 3.1 Measurement of objective well-being: regional social progress index (SPI)

One of the major challenges of this work is the measurement of objective well-being in regions. In general, the last three decades have seen many efforts to develop objective measures of well-being that move ‘beyond GDP’, at least at the national level (Barrington-Leigh and Escande 2018; Domínguez-Torreiro 2016). A prominent example is the Human Development Index (HDI), which was introduced in the 1990s by the United Nations (Beltrán-Estève et al. 2023). Despite these important initiatives, the HDI and other beyond GDP’ indicators typically suffer from three problems:

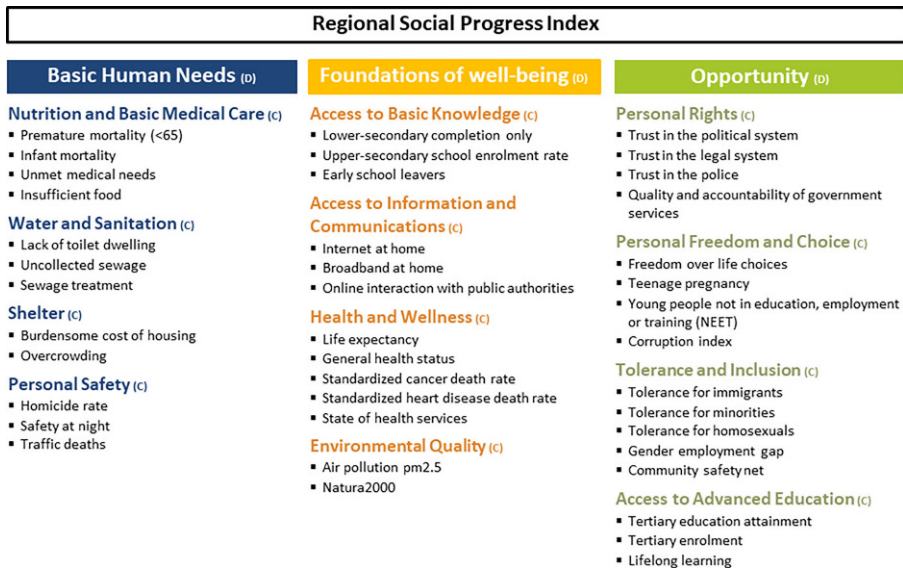
1. They include GDP or other income-based indicators, which can therefore mask a lack of social progress in economically strong countries such as Saudi Arabia (Fehder et al. 2018).
2. They are only available at the national level, despite some important exceptions (e.g. D’Urso et al. 2020; Ferraz et al. 2020; Lenzi and Perucca 2020; Peiró-Palomino et al. 2020), thus generally ignoring potential regional differences (Tomaney 2017).
3. In addition to aggregated measures, there are also more domain-specific indicators that focus on specific aspects such as environmental sustainability (e.g. the Ecological Footprint introduced by Wackernagel and Rees (1998)) and thus lack generality, although they are informative (Fehder et al. 2018).

To overcome these issues, this article uses the Social Progress Index (SPI) developed by the non-profit organization Social Imperative Network<sup>7</sup> (Fehder et al. 2018; Porter et al. 2014). This multidimensional measure is based solely on non-income-based indicators and thus allows for a systematic examination of the relationship between economic development (e.g. proxied by GDP per capita) and social development (Annoni and Bolsi 2020). While previous versions of the SPI are primarily available at the national level (e.g. Peiró-Palomino et al. 2023), this study uses the regional EU-SPI version, which calculates the SPI at the NUTS-2 level (Annoni et al. 2016). However, the regional EU-SPI is only available for the years 2016 and 2020 (Beltrán-Estève et al. 2023). Since the research focus of this paper tends to require longitudinal data, the procedure of Annoni et al. (2016) is therefore replicated for a longer period of time. Unfortunately, due to data limitations in terms of available indicators and years, the procedure of Annoni et al. (2016) had to be slightly adapted and the available period of the regional EU-SPI is limited between 2011 and 2018. However, in general the changes are rather minor and are noted throughout

<sup>7</sup> For more information about the organization, please see: <https://www.socialprogress.org/>.

this section. The similarity and consistency can also be seen in the correlation: The SPI measure of Annoni et al. (2016) is strongly correlated with the mean of the SPI variable presented here (correlation coefficient: 0.96).

The SPI builds conceptually on the capabilities approach by Sen (1985b), presented in Sect. 2.1, and is thus essentially related to the concept of objective well-being. The index defines social progress as “(...) the capacity of a society to meet the basic human needs of its citizens, establish the building blocks that allow citizens and communities to enhance and sustain the quality of their lives, and create the conditions for all individuals to reach their full potential.” (Fehder et al. 2018, p. 479). The definition refers to three core elements of social progress, called dimensions: (i.) Basic Human Needs, which encompasses the capacity of a country/region to meet the basic human needs of its citizens; (ii.) Foundations of well-being, which go a step further by capturing the building blocks that enable citizens and communities to improve and sustain their quality of life; (iii.) Opportunities, which encompasses the opportunities for all individuals to reach their full potential (Annoni et al. 2016; Fehder et al. 2018; Stern et al. 2015). In line with previous studies (e.g. Annoni and Bolsi 2020; Fehder et al. 2018), each of these dimensions can then be further divided into four components. Finally, each component consists of two to five indicators.<sup>8</sup> The SPI is therefore a multidimensional and output-oriented index for objective well-being (Annoni et al. 2016; Beltrán-Estevé et al. 2023). Figure 1



**Fig. 1** Framework for the Regional Social Progress Index (SPI)—Dimensions (D) and Components (C)

<sup>8</sup> Due to limited access to data from the EU-SILC database and the European Environment Agency (EEA), two components (i.e. Shelter and Environmental Quality) are only based on an aggregation of two indicators. However, given that this is only a small deviation from the procedure used by Annoni et al. (2016), it is reasonable to assume that the results are not significantly affected by this.

provides a comprehensive overview of the three underlying dimensions of the SPI, their four components, and the indicators for each component.

As can be seen from Fig. 1, a diverse data basis is required for the construction of the SPI. The following databases were used in this context: Eurostat, EU-SILC, EEA, European Social Survey, European Quality of Institutions Index Survey, and the European Value Survey. A detailed list of the different data sources can be found in the Appendix (see Table 3).

Based on these different sources of information, the step-by-step procedure of Annoni et al. (2016) is followed to construct the SPI in a transparent and consistent manner. One of the main challenges is to reach the sub-national NUTS-2 level for the variety of indicators. To achieve this, Annoni et al. (2016) proposed the rule that within and across components at least half of the respective indicators must be at the NUTS-2 level. For example, if at least 50% of the indicators in the Nutrition and Basic Medical Care component are available at the NUTS-2 level, then the resulting component is considered to be representative at this level. If indicators are not available at NUTS-2 level, a less aggregated level such as NUTS-1 or national level is used. Consequently, the within-country variability of the resulting SPI and its sub-indices is rather underestimated (Annoni et al. 2016). However, in general, this “50%” rule only had to be applied to 3 out of 12 components. As a second step, the internal consistency of each of the twelve components is tested by verifying that there is a strong multivariate correlation among the underlying indicators. Since the majority of the indicators used here are identical to those from the work of Annoni et al. (2016)<sup>9</sup>, which already empirically showed internal consistency, it is very likely that this will also be the case for this specific study. This is especially true since the SPI has been shown to be robust to different designs (Beltrán-Estevé et al. 2023). Nevertheless, in line with previous studies (e.g. Annoni et al. 2016), the internal consistency is also verified by a principal component analysis (PCA) for the indicators (Rencher and Christensen 2012). As can be seen in the Appendix (see Figs. 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15), the results generally confirm the internal consistency. As a next step, the SPI scores at all levels (i.e. indicators, components, dimensions, overall) are normalized and range from a 0–100 scale by using the min-max transformation with indicator-specific boundaries (Annoni and Bolsi 2020). Following previous studies (e.g. Annoni et al. 2016; Beltrán-Estevé et al., 2023), these limits are based on theoretical utopian and dystopian values, or maximum and minimum values over a time series (where available). The corresponding transformation can be expressed as follows:

$$X_{normalized} = \begin{cases} \frac{100 \cdot (x - x_{min})}{(x_{max} - x_{min})} & \text{if } x \text{ is positively oriented} \\ \frac{-100 \cdot (x - x_{min})}{(x_{max} - x_{min})} + 100 & \text{if } x \text{ is negatively oriented} \end{cases} \quad (1)$$

A widely discussed issue in the case of composite indices relates to the aggregation of indicators. However, there is not a one-size-fits-all approach that is valid in every context (Annoni and Bolsi 2020; Decancq and Lugo 2013). Given the specific research context and the good internal consistency of the indicators identified ear-

<sup>9</sup> See Table 3 in the Appendix.

lier, in this study a hybrid aggregation method is applied (Decancq and Lugo 2013) that includes the arithmetic mean within each component and the generalized mean across components and across dimensions. The good internal consistency ensures that the arithmetic mean is an appropriate way of aggregating within dimensions, as the compensability effect, i.e. poor scores on some indicators being offset by high scores on others, is limited across indicators (Annoni et al. 2016; Annoni and Bolsi 2020). The score within each component  $c$  in region  $r$  and year  $t$  can therefore be expressed as follows:

$$c_{rt} = \bar{x}_{rt} = \frac{1}{n} \sum_{i=1}^n (x_i) \quad (2)$$

where  $\bar{x}_{rt}$  is the arithmetic mean of all underlying indicators of component  $c$  in region  $r$  and year  $t$ .

However, the compensatory effect is generally more pronounced across components, and especially across dimensions. Therefore, in these two cases, an inequality-adverse type of aggregation is applied by calculating the generalized mean, which is between the arithmetic ( $p=1$ ) and the geometric average ( $p=0$ ), helping to mitigate the compensatory effect (Annoni et al. 2016; Annoni and Bolsi 2020; Decancq and Lugo 2013). By using the generalized mean, the score for dimension  $j$ , i.e. basic human needs, foundations of well-being, or opportunities, in region  $r$  and year  $t$  can be computed as:<sup>10</sup>

$$D_{jrt}^{(\beta)} = \begin{cases} \left( \frac{1}{n} \sum_{i=1}^n C_{irt}^{\beta} \right)^{\frac{1}{\beta}} & \text{for } \beta \neq 0 \\ \left( \prod_{i=1}^n C_{irt} \right)^{\frac{1}{n}} & \text{for } \beta = 0 \end{cases} \quad (3)$$

where  $C_{irt}$  is the underlying component  $i$  within dimension  $j$  in region  $r$  and year  $t$ . The  $\beta$  (of  $n$  components) is a parameter that can be used to control the level of compensability. While in the case of  $\beta=1$ , the generalized mean is equal to the arithmetic, for  $\beta=0$ , it is the geometric mean (Annoni et al. 2016; Annoni and Bolsi 2020; Beltrán-Estevé et al. 2023). When  $\beta<0$  and  $\beta>1$ , the generalized mean is considered to be inequality-adverse (Ruiz 2011). Following the results of the Monte-Carlo simulation on the impact of different values of  $\beta$  by Annoni et al. (2016),  $\beta$  is set to 0.5, which allows the index to be partially non-compensatory (Annoni and Bolsi 2020). A key challenge in creating a multidimensional measure such as the SPI is missing values. Despite best efforts to minimize this problem, there are unfortunately occasions when this is simply not possible. The final dataset therefore excludes regions with more than two missing values in more than three components, which is in line with Stern et al. (2015). As a result, the SPI could be calculated for 177 NUTS-2 regions from eleven European countries.

<sup>10</sup> The same applies to the aggregation across dimensions.

### 3.2 Main independent variables

As discussed in Sect. 2, the economic growth and the underlying industrial structure are assumed to be drivers of the regional SPI. Since the SPI does not include any income-based measure, it is possible to examine the influence of the economic growth of regions (Fehder et al. 2018). To measure economic growth, researchers have traditionally used GDP per capita (Costanza et al. 2018; Giovannini and Rondinella 2018). In line with this tradition, information about the GDP per capita in NUTS-2 regions is collected from Eurostat and added to the regional dataset. Since the underlying distribution is skewed, the logged GDP per capita is used (*GDPpc\_ln*).

Despite the popularity of the cluster concept, there are still definitional inconsistencies (Martin and Sunley 2003) and, as a result, a variety of different measures to empirically identify clusters (Brenner 2017; Delgado et al. 2016). Most cluster definitions emphasize spatial linkages, thematic connections, and interdependencies as core elements (Grashof and Fornahl 2021), which is also in line with the underlying cluster understanding in this study. The used empirical identification of industrial clusters also reflects these core elements. It builds on the industrial aggregation into cluster categories developed by the U.S. cluster mapping project (Porter 2003; Delgado et al. 2014), which has then been translated into the respective European industrial classifications (Ketels and Protsiv 2014). The underlying industries are in a first step grouped into ‘traded’ (geographically concentrated) or ‘local’ industries (geographically dispersed). In a second step, the traded industries are further grouped into 51 related industry groups, so called cluster categories, based on co-location, similarity in skill use and input-output relationships (Ketels and Protsiv 2021).<sup>11</sup> Hence, these industrial clusters capture quite well the core elements of most common cluster definitions (Grashof and Fornahl 2021). An additional advantage is that these clusters directly reflect the regional industrial structures, which seems best suited to the research focus of this article on objective well-being (see Sect. 2). The underlying comprehensive data is provided by the European Cluster Observatory. Based on this, the location quotient (LQ) of employment in each cluster category is calculated. The LQ in each region  $r$ , in each cluster category  $c$ , and year  $t$  is calculated as follows:

$$LQ = \frac{\text{employment}_{r,c}^t / \sum_c \text{employment}_{r,c}^t}{\sum_r \text{employment}_{r,c}^t / \sum_r \sum_c \text{employment}_{r,c}^t} \quad (4)$$

where  $\text{employment}_{r,c}^t$  is the number of employees in region  $r$  in a cluster category  $c$  at a specific time  $t$ ,  $\sum_c \text{employment}_{r,c}^t$  is the total number of employees in region  $r$  at a specific time  $t$ ,  $\sum_r \text{employment}_{r,c}^t$  is the sum of all employees in each cluster category  $c$  in every region  $r$  at time  $t$ , and  $\sum_r \sum_c \text{employment}_{r,c}^t$  is the sum of all employees in every region  $r$  at time  $t$ . Following the procedure by previous studies (e.g. Delgado et al. 2012; Ketels and Protsiv 2016), the regional LQ needs to belong to the top 20% in each cluster category and at least 500 employees need

<sup>11</sup> A list of the corresponding cluster categories with the underlying four-digit NACE industry classifications can be found in Table 4 in the Appendix.

to be active in the corresponding regional cluster category. Only when this is the case, we speak of an industrial cluster. This ensures that industrial clusters have a critical mass and are robust. Moreover, such a quantile-based cut-off is also better capable of considering the different distributions of LQs across the various cluster categories (Ketels and Protsiv 2021). The diversity of the industrial cluster landscape in a region is then calculated by counting the number of different cluster categories in the corresponding NUTS-2 regions that meet the previously described absolute and relative thresholds (*Number industrial clusters*). This variable can have a theoretical maximum of 51, indicating that a region is specialized in all related industries (i.e. cluster categories), and a minimum of zero. In other words, a higher number of different industrial clusters means that the industrial landscape within a NUTS-2 region is quite diverse, while a low number refers to a regional industry structure that is more specialized in selected related industries.

In line with the procedure by Ketels and Protsiv (2016), these industrial clusters can be further differentiated according to their strength, which they call ‘performance stars’. As indicated in Fig. 16 in the Appendix, regions can get two additional ‘performance stars’ for each of the potential 51 industrial clusters in terms of size, capturing the critical mass of the cluster, and productivity, capturing the (static) performance. In order to receive a ‘performance star’ in terms of size, a specific industrial cluster of a region must be among the top 20% of all European regions in terms of the number of employees and establishments. In the case of productivity, an industrial cluster must belong to the top 20% of all European regions in terms of wages, which are adjusted for local cost levels (Ketels and Protsiv 2016). To calculate the strength of industrial clusters, the number of ‘performance stars’ is divided by the total number of different industrial clusters (*Strength industrial clusters*). High values indicate that the existing industrial cluster structure is relatively strong, while low values indicate the opposite. Since a region can only get two ‘performance stars’ per industrial cluster, the theoretical maximum of this variable is 2.

### 3.3 Control variables

In addition, several regional-level control variables are considered. First, to account for the overall knowledge stock of a region, the weighed number of patents based on the share of inventors (*Regional Inventor’s Share*) is calculated. To further control for the underlying technological structure in the regional economies, the number of technological specializations (on the four-digit CPC level) is estimated (*Number Technological Specializations*). Moreover, in line with previous studies (e.g. Garcia-Vega 2006), the technological diversity of regions is additionally considered by calculating the inverse Herfindahl-Hirschman Index (HHI), which is calculated as follows:

$$D_i = \sum_i p_i^2 \quad (5)$$

where  $p_i$  is the share of inventive activity (inventor-based) in a region in each technology field  $i$ , based on the 35 technology fields classified by Schmoch (2008).



The inverse HHI,  $D_i$ , ranges thereby from zero, i.e. no diversity, to one, i.e. maximum diversity. The necessary patent data for these three control variables are taken from the OECD Regpat database. Besides these patent-related measures, it is also controlled for the employment situation within a region which is likely to be important for the objective well-being (Stiglitz 2002; De Witte et al. 2015). Based on information from Eurostat, the economic activity rates (in %) from 15 to 74 years in age is therefore used as a control variable (*Economic Active Population Share*). Furthermore, it is controlled for the regional age structure by considering the median age (in years) of the regional population (*Age of Population*). In addition, population density is included to control for urbanization, which has been shown to be influential in terms of subjective well-being (e.g. Lenzi and Perucca 2020; Winters and Li 2017). As the underlying distribution is skewed, the logged population density is used (*PopDens\_In*). Lastly, the diversity of the corresponding regional industrial structure is considered by counting the number of different traded industries based on employment data from the European Cluster Observatory (*Diverse Industry Structure*).

As a result, the final database consists of 165 NUTS-2 regions from 11 EU countries (for the time period between 2011 and 2018).<sup>12</sup> The descriptive statistics of the above-mentioned variables are reported in Table 5 in the Appendix. In addition, the pairwise correlation matrix is presented in Table 6 in the Appendix. Since the correlation between the variables is rather low to medium, multicollinearity appears not to be a serious problem.

### 3.4 Methodological approach

In order to empirically investigate the assumed relationships presented in Sect. 2, the econometric approach must adequately address some obstacles in terms of endogeneity. For example, since the current level of objective well-being likely depends on previous levels of itself, the problem of autocorrelation may occur. Consequently, dynamic panel models are applied using generalized method of moments (GMM). Following previous studies (e.g. Damioli et al. 2021), a system GMM approach (Blundell and Bond 1998) with two-step robust standard errors (Arellano and Bond 1991; Windmeijer 2005) is used, which can be expressed in the following stylized way:

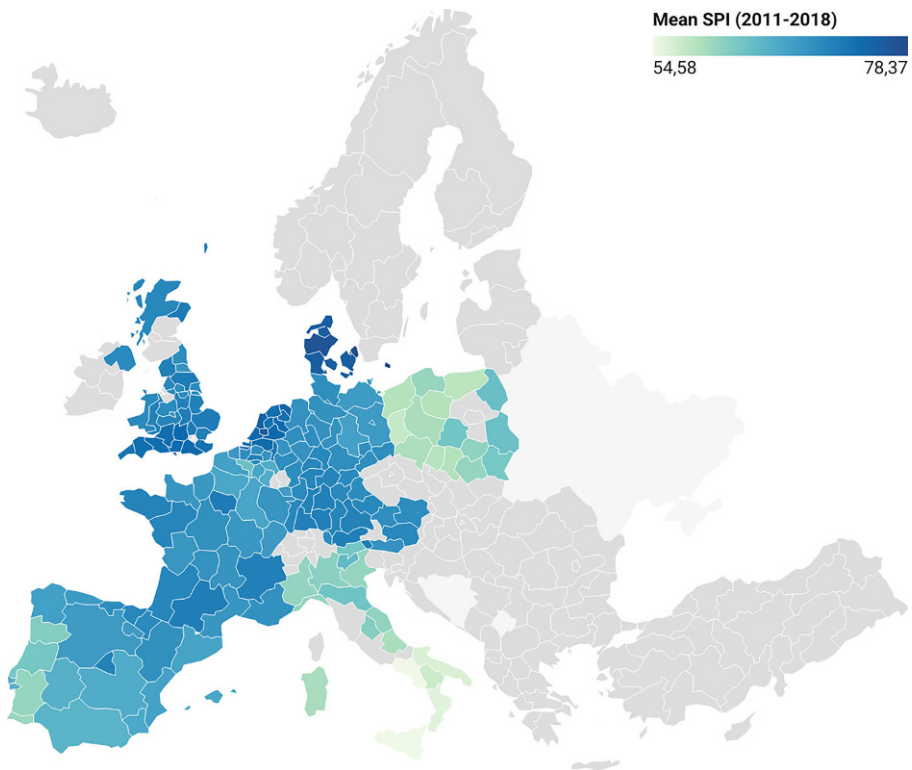
$$\begin{aligned} SPI = & \alpha + \beta_1 SPI_{it-1} + \beta_2 GDPpc\_ln_{it-1} + \beta_3 NumberIndustrialClusters_{it-1} \\ & + \beta_4 Strength\ Industrial\ Clusters_{it-1} + \beta_5 Controls_{it-1} + \gamma_i + \omega_i \quad (6) \\ & + \delta_t + \varepsilon_{it} \end{aligned}$$

where the dependent variable  $SPI$  is the Social Progress Index in region  $i$  at year  $t$ . Since it is expected that the influence of the explanatory variables on  $SPI$  will likely need some time to unfold, a one-year time lag is included. The implementation of this lag structure also mitigates, at least to some extent, the potential problem of

<sup>12</sup> During the merging process, twelve NUTS-2 regions were dropped due to a lack of information on the industrial cluster structure in these regions.

reverse causality.<sup>13</sup> The main variables of interest refer to the lagged logarithm of GDP per capita, the lagged number of industrial clusters and the lagged strength of industrial clusters in region  $i$  at year  $t$ . The controls include the regional inventor's share, the number of technological specializations, the inverse HHI, the economic active population share, the number of different industries, the population's median age and the logarithm of population density (all lagged by one-year time).  $\alpha$  is the intercept,  $\gamma_i$  denotes the region fixed effects,  $\omega_i$  indicates the country fixed effects,  $\delta_t$  represents the year fixed effects and  $\varepsilon_{it}$  reflects the error term.

For the implementation of the system GMM approach, the Stata command `xtabond2` is used (Roodman 2009). In this approach, the median age of the regional population, the (logged) population density, the country dummies and year dummies are treated as strictly exogenous.



**Fig. 2** Geographical distribution of the mean SPI in Europe (2011–2018)

<sup>13</sup> As a further test, the dependent variable, SPI, is swapped with the main independent variables. As shown in Table 7 in the Appendix, the influence of SPI on GDP per capita and the number of industrial clusters is statistically insignificant. It is only in the case of the strength of the industrial clusters that a slightly significant influence is found ( $p$ -value: 0.095). In general, therefore, the results of these robustness checks provide a first indication that the problem of reverse causality may not be too severe.

**Table 1** Descriptive statistics of main variables by percentiles of SPI distribution

Percentile (in terms of SPI)	SPI		GDPpc (logarithm)		No. Cluster		Cluster Strength	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
1st	58.14	2.15	9.54	0.43	12.29	5.36	3.14	1.34
2nd	63.95	1.48	9.90	0.37	8.79	4.81	2.80	1.23
3rd	67.12	0.59	10.14	0.23	7.54	2.52	2.95	1.19
4th	68.52	0.29	10.27	0.18	7.87	2.78	2.98	1.20
5th	69.35	0.21	10.32	0.22	7.84	2.79	3.09	1.18
6th	70.04	0.17	10.41	0.22	8.87	2.63	3.09	1.16
7th	70.64	0.20	10.42	0.22	8.93	2.57	3.06	1.16
8th	71.44	0.31	10.43	0.23	8.81	2.49	2.47	0.85
9th	72.79	0.50	10.48	0.26	8.16	2.51	2.53	0.81
10th	75.59	1.38	10.56	0.23	8.47	2.52	2.74	1.20

## 4 Empirical results and discussion

### 4.1 Descriptive results

In order to get first insights about the geographical distribution of the regional objective well-being in Europe, Fig. 2 depicts the average SPI across NUTS-2 regions. As can be seen in Fig. 2, apart from some missing regions due to data limitations (shaded gray), there is considerable regional variation in terms of the (average) SPI. In line with previous research on the regional distribution of subjective well-being (e.g. Puntscher et al. 2015) particularly regions from Denmark (Hovedstaden has thereby the highest score), but also from the Netherlands (Utrecht has an SPI score of 76.42), have on average a relatively high SPI. Interestingly, there are also differences within nations that correspond to well-known disparities in economic development, such as between northern and southern Italy.

This can be further explored in Table 1, which presents the mean and standard deviation by percentiles of the SPI distribution for the main variables of interest (i.e. SPI, GDP per capita, the number and strength of industrial clusters).

Looking at the mean of the SPI along the percentiles confirms the previous observation of regional differences in objective well-being. Moreover, it can be seen that the mean of GDP per capita consistently increases across the percentiles of SPI. In other words, regions with relatively high SPI scores are also the ones that perform comparatively good in terms of GDP per capita. While the relationship between the average SPI and the average GDP per capita is relatively straightforward, the relationship between the average SPI and the average number of different industrial clusters and the average strength of industrial clusters is less clear. Both variables show rather inconsistent patterns across the percentiles of SPI. While the highest mean can be found in the 1st percentile of SPI (No. Cluster: 12.29; Cluster Strength: 3.14), the second highest means can be found in the middle (5th to 6th in the case of Cluster Strength) to upper (7th in the case of No. Cluster) percentile of SPI.

These rather descriptive analyses can of course only provide first insights about the relationship between SPI, GDPpc, the number of industrial clusters and their

**Table 2** Regression results from system GMM approach

	SPI (1)	SPI (2)	SPI (3)	SPI (4)
GDPpc_ln	2.916*** (0.840)	2.866*** (0.730)	2.796*** (0.824)	2.937*** (0.662)
Number industrial clusters	—	0.058*** (0.018)	—	0.162*** (0.055)
Strength industrial clusters	—	—	−0.135 (0.128)	0.241 (0.208)
Number industrial clusters* Strength industrial clusters	—	—	—	−0.039** (0.017)
SPI	0.380*** (0.075)	0.385*** (0.068)	0.404*** (0.071)	0.361*** (0.079)
Regional Inventor's Share	−0.00001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.00003 (0.0002)
Number Technological Specializations	0.002 (0.003)	0.003 (0.004)	0.004 (0.003)	0.005 (0.003)
Inv_HHI	−1.402 (1.178)	−1.744 (1.375)	−1.430 (1.142)	−2.233* (1.177)
Economic Active Population Share	0.097* (0.055)	0.061 (0.050)	0.076 (0.049)	0.076 (0.050)
Age of Population	0.111*** (0.033)	0.102*** (0.039)	0.094*** (0.035)	0.113*** (0.038)
Diverse Industry Structure	0.006 (0.067)	0.028 (0.073)	0.004 (0.070)	−0.057 (0.080)
PopDens_ln	0.044 (0.139)	−0.016 (0.150)	0.005 (0.147)	0.041 (0.136)
Constant	1.771 (7.097)	3.523 (6.511)	3.583 (6.982)	6.300 (6.836)
Time-fixed effects	Yes	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes
Observations	705	705	705	705
AR(1)— <i>p</i> value	0.000	0.000	0.000	0.000
AR(2)— <i>p</i> value	0.286	0.402	0.358	0.605
Hansen test— <i>p</i> value	0.262	0.618	0.681	0.945

Note: Two-step robust standard errors (GMM) in parentheses. A one-year time lag is applied for all independent variables

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

strength. However, they do not allow any statistically meaningful conclusions to be drawn. Therefore, the next section examines these relationships in more detail using an econometric approach that controls for additional regional characteristics that may be relevant.

## 4.2 Econometric results

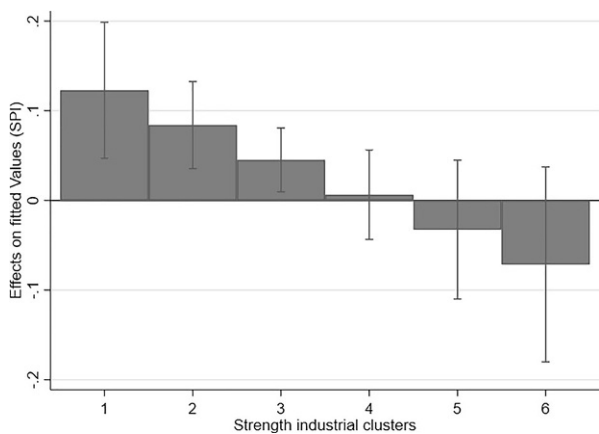
The results of the system GMM approach (Blundell and Bond 1998) with two-step robust standard errors (Arellano and Bond 1991; Windmeijer 2005) are presented in Table 2. In general, the control variables are mostly stable throughout the models. As expected, the previous level of the SPI significantly influences the current level of the SPI, supporting the decision to use a dynamic panel approach. Moreover, a highly significant positive influence of the *Age of Population* is found in all models, indicating that regions with an older median age structure also have higher objective well-being.

With regard to the main variables of interest, a significant positive influence of *GDPpc\_ln* is found in Model 1, which remains robust in all subsequent models. Consistent with recent findings at the national level (e.g. Fehder et al. 2019), high income levels are therefore associated with overall high levels of objective well-being.<sup>14</sup> Hence, Hypothesis 1 cannot be rejected.

In Model 2, the influence of the number of different industrial clusters (i.e. diverse cluster portfolio) is examined. The variable *Number industrial clusters* is statistically significant and positive. As assumed (see Hypothesis 2), a broad portfolio of different industrial clusters is positively associated with the objective well-being in regions. This finding is consistent with previous research indicating that a diverse industrial structure broadens occupational and consumption choices, thereby promoting objective well-being (Ali and Cantner 2020; Clark 2005; Hartmann and Pyka 2013). Hence, Hypothesis 2 cannot be rejected.

Since the effects of industrial clusters may vary according to their composition (e.g. Delgado et al. 2014; Grashof 2020), in Model 3, the influence of the strength of industrial clusters is tested. Contrary to what was assumed in Sect. 2 (see Hypoth-

**Fig. 3** Average marginal effects of lagged number of industrial clusters on SPI across different levels of the strength of industrial clusters (with 95% CIs)



<sup>14</sup> In light of the discussion of the Easterlin Paradox in the case of subjective well-being (e.g. Easterlin 1974; Stevenson and Wolfers 2013), a further robustness check (see Table 8 in the Appendix) tests for potential non-linear effects in this context. The corresponding results do not suggest that this is the case for objective well-being.

esis 3), the corresponding coefficient is negative and insignificant. The strength of the industrial cluster structure does therefore not significantly promote the objective well-being in regions. Consequently, Hypothesis 3 has to be rejected.

To better understand the interplay between the number and strength of industrial clusters, an interaction effect between them is also tested (see Model 4). The corresponding results show that there is a significant negative interaction term, implying a substitution effect. However, as can be seen from the insignificant coefficient of the variable *Strength industrial clusters* in Model 4 in Table 2 (when the variable *Number industrial clusters* equals zero), regions with a highly specialized and strong industrial cluster structure do not significantly promote the objective well-being in regions. Instead, by plotting the average marginal effects of the number of different industrial clusters (see Fig. 3), it can be shown that the positive influence of a diverse cluster portfolio (i.e. diverse industrial structure) is reduced by the strength of industrial clusters.

Given that cluster strength captures the absolute size and productivity, this negative moderating influence may refer to size-based negative externalities or in other words diseconomies of agglomeration (McCann and Folta 2008), as already indicated in Sect. 2.3. While the cluster size has been shown to be an influential variable for firm performance (e.g. Folta et al. 2006; Grashof et al. 2019), there is also evidence of size-based negative externalities in the context of subjective well-being (e.g. Morrison 2011; Sander 2011). Since these negative externalities can include increased cost of living, pollution, and crime (Prevezer 1997; Winters and Li 2017), it is also likely that objective well-being is negatively affected, offsetting the potential positive economic impacts of strong industrial cluster structures (e.g., Slaper et al. 2018).

Overall, the results show that the regional economic growth is a strong predictor of the objective well-being in regions. Moreover, the corresponding industrial structure within regions is an additional driver of objective well-being. In particular, regions with a diverse cluster portfolio have high objective well-being, since they can provide broad occupational and consumption choices for example. However, this positive influence is negatively moderated by the strength of industrial clusters, possibly due to size-based negative externalities.

## 5 Conclusion

Promoting the well-being of people is the ultimate aim of all EU social and economic policies (Domínguez-Torreiro 2016; Eurostat 2015). However, research in this area has been mainly limited to income-based measures of well-being, such as GDP per capita (Castellacci 2023; Hartmann and Pyka 2013). Following previous “beyond GDP” initiatives (e.g. Fleurbaey 2009; Stiglitz et al. 2009), this study aims to move beyond income-based measures and investigate the spatial distribution as well as drivers of objective well-being in European regions. It thereby responds to recent studies that call for more research on well-being at the regional level (Tomaney 2017; Peiró-Palomino et al. 2020). Based on the capabilities approach (Sen 1985b) and the framework of the EU Regional Social Progress Index (SPI), the objective well-

being is measured at the NUTS-2 level for the period between 2011 and 2018. By combining this with further information about the economic, industrial and knowledge structure in regions coming from several data sources (e.g. Eurostat, European Cluster Observatory, OECD Regpat), the relationship between objective well-being, economic growth and industrial clusters is empirically investigated using a system GMM approach (Blundell and Bond 1998).

In summary, this study provides three main findings. First, it is shown that economic growth increases objective well-being in regions. Thus, there is no evidence of the Easterlin paradox as in the case of subjective well-being (e.g. Easterlin 1974; Stevenson and Wolfers 2013). Second, regions with a high number of different industrial clusters, i.e. a diverse cluster portfolio, are more likely to have high objective well-being. Third, however, this influence is negatively moderated by the strength of the industrial clusters. Hence, the influence of industrial cluster structures on objective well-being in regions is more complex than initially assumed. Regional cluster structures that are not overly specialized in a few large industries, but instead consist of diverse industries, appear to be more likely to achieve higher levels of objective well-being.

However, this study is not without its limitations, which provide an opportunity for further research. First of all, while it is indeed one of the contributions of this study to examine the regional distribution and drivers of objective well-being at the NUTS-2 level, this is still a relatively broad geographical level of analysis. Although previous studies have also used similar data at this level of analysis (e.g. Ketels and Protsiv 2021), future studies could try to go beyond the underlying data limitations of this study (especially regarding the SPI) and investigate objective well-being at a more nuanced geographical level, such as labor market regions. Moreover, in view of the focus of this study, the influence of related industry structures is analyzed (i.e. cluster categories by Ketels and Protsiv 2021). Since same-industry concentrations in more narrowly defined industry classes may lead to different results, e.g. due to co-location with very close competitors from the same industry (Frenken et al. 2015), it seems interesting for future research to also consider a more detailed industry level. Furthermore, given that no single approach can fully capture well-being (D'Urso et al. 2020; Maggino 2016), future research could integrate the objective measure of regional well-being used here with subjective measures of well-being, such as life satisfaction (Castellacci 2023).<sup>15</sup> Moreover, although composite indicators have been widely used to measure the multidimensional phenomenon of well-being, they also have some drawbacks especially in disentangling the underlying mechanisms (D'Urso et al. 2020; OECD 2008). While the overall goal of this study is to provide initial statistical evidence of potential drivers of objective well-being at the regional level, future studies may examine in detail the individual dimensions or indicators of the SPI and thereby attempt to further disentangle the underlying mechanisms by which objective well-being is shaped in regions. In this context, it also seems interesting for future studies to examine alternative characteristics, such as institutional and technological ones, that may influence the objective well-being of regions.

<sup>15</sup> At the same time, however, it could be argued or criticized that the SPI also relies in part on citizens' subjective perceptions, especially in the opportunity dimension (Beltrán-Estevé et al. 2023).



Furthermore, given the relatively short time span of the database, potential long-term effects of economic growth on objective well-being cannot be adequately examined in this study and must therefore be left open for future research. Lastly, although the sources of endogeneity have been addressed as good as possible by using dynamic panel models, implementing a lag structure and conducting several robustness checks (e.g. switching the dependent variable with the main independent variables), endogeneity cannot be completely ruled out. Since the underlying mechanisms are not explicitly identified in this study, the empirical results may therefore not be interpreted as true causal effects, but in a more conservative way as associations despite the applied dynamic panel models using GMM.

Nevertheless, despite these limitations, it can be concluded that the empirical findings on the relationship between objective well-being, economic growth and industrial clusters in regions contribute to the regional and innovation economics literature. By quantitatively examining the drivers of objective well-being in regions, this study provides a more comprehensive understanding of regional performance and sheds light on an often-overlooked topic, particularly at the regional level (e.g. Tomaney 2017). Moreover, this study empirically confirms that economic growth (measured in terms of GDP per capita) is a strong predictor of objective well-being in regions, but also shows that this is far from the whole story. Instead, the corresponding industrial cluster structures within regions also play a relevant role for objective well-being in regions, thereby enriching previous literature on well-being (e.g. Peiró-Palomino et al. 2020) and industrial clusters (e.g. Rocha et al. 2020). These findings have also implications for (regional) policy makers. While supporting overall economic growth appears to be strongly related to objective well-being, the specific regional industrial structure can also have negative socio-economic consequences that regional policies should take into account. In this context, regional policies should prefer to support a diverse industrial cluster portfolio rather than a regional cluster structure that is overly specialized in relatively few large industries.

## 6 Appendix

**Table 3** Overview of data sources and indicators used for the SPI

Dimension	Component	Indicator	Description	Geographical level	Source	Used in Annoni et al. (2016)
1. Basic Human Needs	1. Nutrition and Basic care	Premature mortality (<65)	Mortality rate before age 65	NUTS2	Eurostat	Yes
		Infant Mortality	Ratio of the number of deaths of children under one year of age during the year to the number of live births in that year. The value is expressed per 1000 live births	NUTS2	Eurostat	Yes
	2. Water and Sanitation	Unmet medical needs	Percentage of people declaring having experienced unmet medical needs because: cannot afford (affordability) or long waiting list (efficiency) or too far (accessibility) or didn't know a good doctor (trust/quality)	NUTS2	EU-SILC	Yes
		Insufficient food	Percentage of people declaring their inability to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day	NUTS0	EU-SIIC	Yes
3. Shelter	2. Water and Sanitation	Lack of toilet in dwelling	Share of total population not having indoor flushing toilet for the sole use of their household	NUTS0	EU-SIIC	Yes
		Uncollected sewage	Urban wastewater not collected by collecting systems nor treated by individual or other appropriate systems as % of generated load	NUTS2	EEA	Yes
	3. Shelter	Sewage treatment	Urban wastewater with more stringent treatment as a percentage of collected wastewater	NUTS2	EEA	Yes
		Burdensome cost of housing	Percentage of people living in a dwelling where housing costs (mortgage repayment or rent, insurance and service charges) are a financial burden	NUTS0	EU-SIIC	Yes
		Overcrowding	Percentage of people living in an overcrowded dwelling, as defined by the number of rooms available to the household, the household's size, as well as its members' ages and family situation	NUTS0	EU-SIIC	Yes

**Table 3** (Continued)

Dimension	Component	Indicator	Description	Geographical level	Source	Used in Annoni et al. (2016)
4. Personal Safety		Homicide rate	Rate of homicides per 100 thousand inhabitants (homicide is defined as the intentional killing of a person, including murder, manslaughter, euthanasia and infanticide. It excludes death by dangerous driving, abortion and assisted suicide)	NUTS0	Eurostat	Yes
		Traffic deaths	Number of road traffic accident fatalities per million inhabitants	NUTS2	Eurostat	Yes
		Safety at night	Feeling of safety of walking alone in local area after dark (ranging from 1 [very safe] to 4 [very unsafe]). The average is calculated for each NUTS2 region	NUTS2	ESS	Yes
		Upper-secondary enrolment rate	Enrolment rates of age group 12–18 in upper-secondary or post-secondary non-tertiary education (ISCED 3–4) corrected for population size (aged 15–19)	NUTS2	Eurostat	Yes
2. Foundations of Well-being	1. Access to basic knowledge	Lower-secondary completion only	Percentage of people aged 25 to 64 who have successfully completed at most lower secondary education (ISCED 0–2)	NUTS2	Eurostat	Yes
		Early school leavers	Percentage of people aged 18–24 with at most lower secondary education (ISCED 0–2) and who were not in further education or training during the last four weeks preceding the survey	NUTS2	Eurostat	Yes
		Internet at home	Percentage of households with access to the internet at home	NUTS2	Eurostat	Yes
		Broadband at home	Percentage of households with broadband connection	NUTS2	Eurostat	Yes
2. Access to Information and Communications		Online interaction with public authorities	Percentage of individuals who used the Internet for interaction with public authorities	NUTS2	Eurostat	Yes
		Online interaction with public authorities	Percentage of individuals who used the Internet for interaction with public authorities	NUTS2	Eurostat	Yes

**Table 3** (Continued)

Dimension	Component	Indicator	Description	Geographical level	Source	Used in Annoni et al. (2016)
3. Health and Wellness	Life expectancy		Life expectancy at birth is the mean number of years that a newborn child can expect to live if subjected throughout his life to the current mortality conditions (age specific probabilities of dying)	NUTS2	Eurostat	Yes
	General health status		Self-perceived general health (ranging from 1 [very good] to 5 [very bad]). The average is calculated for each NUTS2 region	NUTS2	ESS	Yes
	Standardized cancer death rate		Standardised death rates for less than 65 years old due to cancer (code C) by 100 000 inhabitants. The standardisation adjusts the death rate to a standard age distribution. The standardised death rates are calculated on the basis of a standard European population, as defined by the World Health Organization	NUTS2	Eurostat	Yes
	Standardized heart disease death rate		Standardised death rate for less than 65 years old due to ischaemic heart diseases (code I) by 100 000 inhabitants. The standardisation adjusts the death rate to a standard age distribution. The standardised death rates are calculated on the basis of a standard European population, as defined by the World Health Organization	NUTS2	Eurostat	Yes
	State of health services		Perceived state of health services in country nowadays (ranging from 0 [extremely bad] to 10 [extremely good]). The average is calculated for each NUTS2 region	NUTS2	ESS	No, but similar
4. Environmental Quality	Air pollution pm2.5		Air Pollution in PM2.5 (average level in $\mu\text{g}/\text{m}^3$ experienced by the population)	NUTS2	EEA & OECD	Yes
	Natura2000		Share of area covered by Natura 2000, a European Union wide network of nature protection areas established under the 1992 Habitats Directive	NUTS0	EEA	Yes

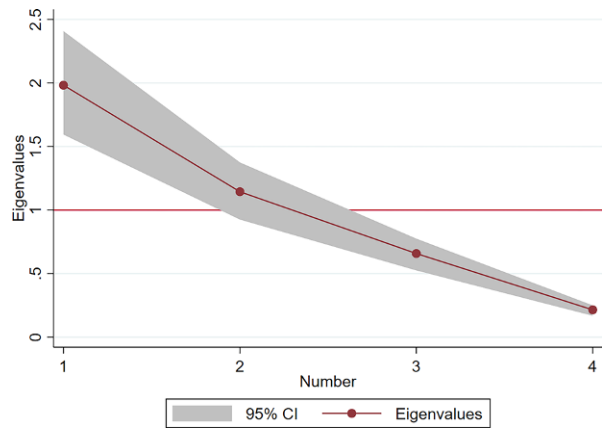
**Table 3** (Continued)

Dimension	Component	Indicator	Description	Geographical level	Source	Used in Annoni et al. (2016)
3. Opportunity	1. Personal rights	Trust in the political system	Trust in politicians (ranging from 0 [No trust at all] to 10 [Complete trust]) and Trust in country's parliament (ranging from 0 [No trust at all] to 10 [Complete trust]). The average is calculated for each NUTS2 region	NUTS2	ESS	No, but similar
		Trust in the legal system	Trust in the legal system (ranging from 0 [No trust at all] to 10 [Complete trust]). The average is calculated for each NUTS2 region	NUTS2	ESS	Yes
		Trust in the police	Trust in the police (ranging from 0 [No trust at all] to 10 [Complete trust]). The average is calculated for each NUTS2 region	NUTS2	ESS	Yes
	2. Personal Freedom and Choice	Quality and accountability of government services	Quality of the government	NUTS2	European Quality of Institutions Index Survey	Yes
		Freedom over life choices	Perceived freedom to decide how to live my life (ranging from 1 [Agree strongly] to 5 [Disagree strongly]). The average is calculated for each NUTS2 region	NUTS2	ESS	Yes
		Teenage pregnancy	Ratio between births from mothers 15–19 and the female population of the same age cohort	NUTS2	Eurostat	Yes
		Young people not in education, employment or training (NEET)	Young people, aged between 15 and 24, neither in employment nor in education and training	NUTS2	Eurostat	Yes
		Corruption Index	Perceived level of corruption	NUTS2	European Quality of Institutions Index Survey	Yes

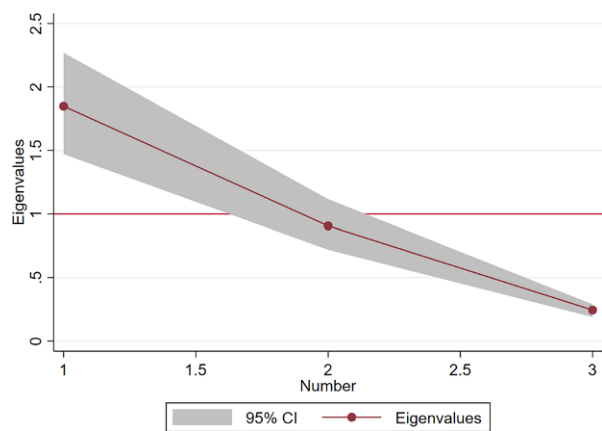
**Table 3** (Continued)

Dimension	Component	Indicator	Description	Geographical level	Source	Used in Annoni et al. (2016)
3. Tolerance and Inclusion		Impartiality of government services	Level of impartiality of government services	NUTS2	European Quality of Institutions Index Survey	Yes
		Tolerance for immigrants	Perceived tolerance for immigrants (based on questions (i.) whether immigration is bad or good for country's economy; (ii.) country's cultural life is undermined or enriched by immigrants; (iii.) immigrants make country worse or better place to live). Each question ranging from 0 (worst) to 10 (best). The average is calculated for each NUTS2 region	NUTS2	ESS	No, but similar
		Tolerance for minorities	Tolerance to become neighbors if they are of a different race, migrants, homosexuals, Jews or Gypsies. Question: don't like as neighbours (...). The average is calculated for each NUTS2 region	NUTS2	EVS	No, but similar
		Tolerance for homosexuals	Perceived evaluation whether gays and lesbians are free to live life as they wish (ranging from 1 [Agree strongly] to 5 [Disagree strongly]). The average is calculated for each NUTS2 region	NUTS2	ESS	No, but similar
		Gender employment gap	Difference between female and male employment rates	NUTS2	Eurostat	Yes
4. Access to Advanced Education		Community safety net	Impact of social transfers (excluding pensions) on poverty reduction	NUTS0	Eurostat	Yes
		Tertiary education attainment	Percentage of population aged 25–64 with tertiary education (ISCED 5–8) attainment	NUTS2	Eurostat	Yes
		Tertiary enrolment	Ratio of tertiary students (ISCED 5–6) to the total population	NUTS2	Eurostat	Yes
		Lifelong learning	Percentage of persons aged 25 to 64 who stated that they received education or training in the four weeks preceding the survey with respect to the total population of the same age	NUTS2	Eurostat	Yes

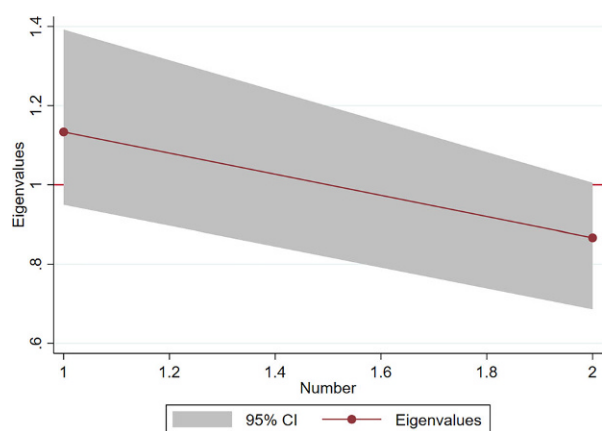
**Fig. 4** Indicators of component “Nutrition and Basic Medical Care” (Scree plot of eigenvalues)



**Fig. 5** Indicators of component “Water and Sanitation” (Scree plot of eigenvalues)

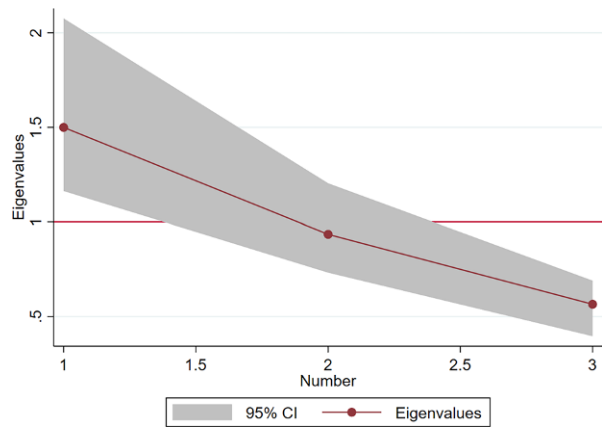


**Fig. 6** Indicators of component “Shelter” (Scree plot of eigenvalues)

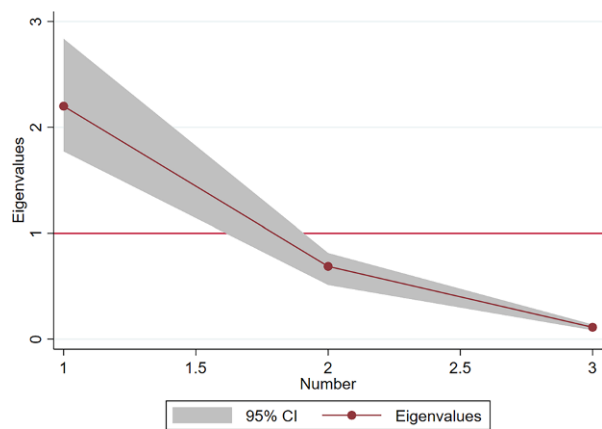




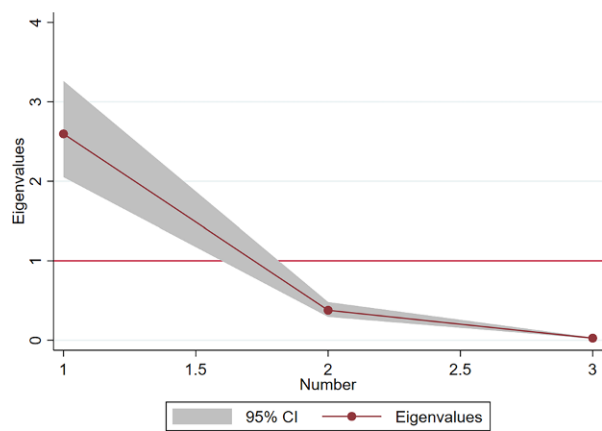
**Fig. 7** Indicators of component “Personal Safety” (Scree plot of eigenvalues)



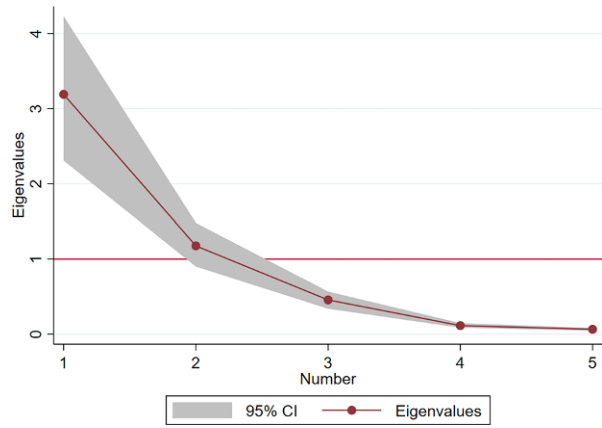
**Fig. 8** Indicators of component “Access to Basic Knowledge” (Scree plot of eigenvalues)



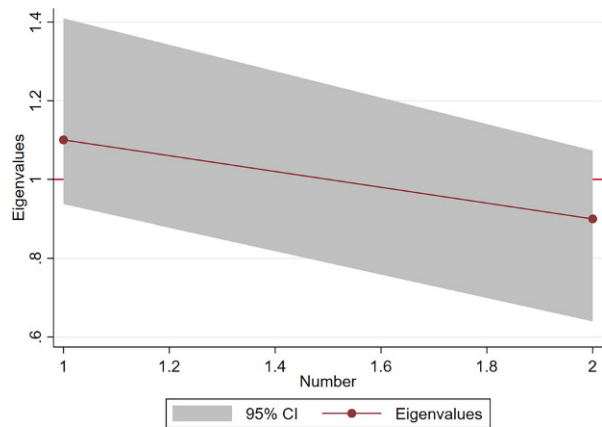
**Fig. 9** Indicators of component “Access to Information and Communications” (Scree plot of eigenvalues)



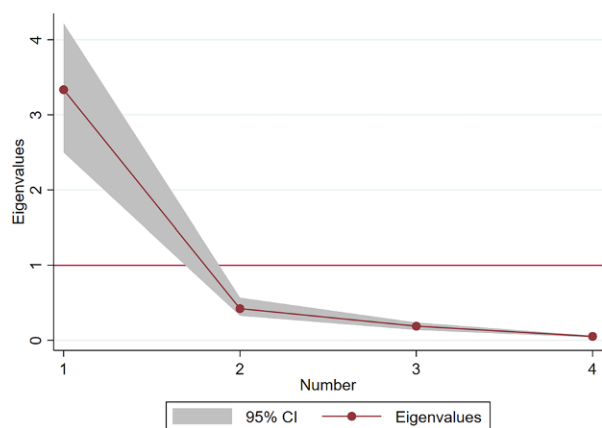
**Fig. 10** Indicators of component “Health and Wellness” (Scree plot of eigenvalues)



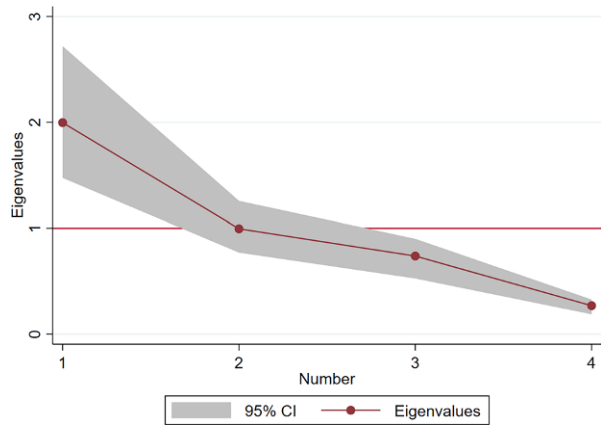
**Fig. 11** Indicators of component “Environmental Quality” (Scree plot of eigenvalues)



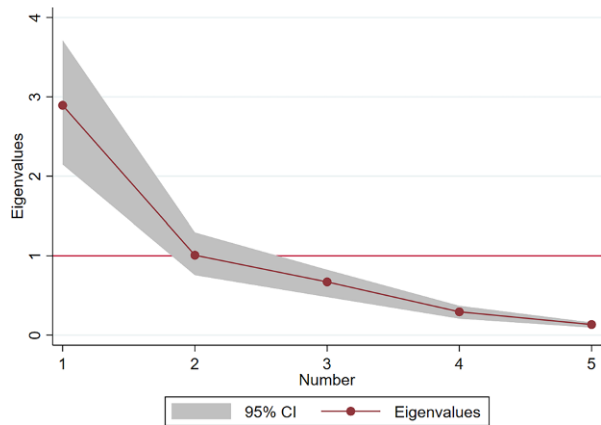
**Fig. 12** Indicators of component “Personal Rights” (Scree plot of eigenvalues)



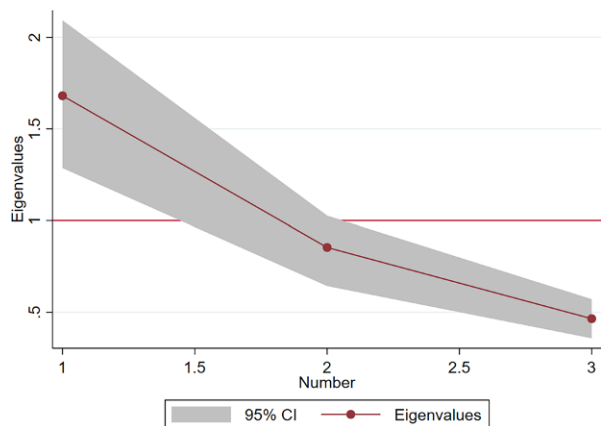
**Fig. 13** Indicators of component “Personal Freedom and Choice” (Scree plot of eigenvalues)



**Fig. 14** Indicators of component “Tolerance and Inclusion” (Scree plot of eigenvalues)



**Fig. 15** Indicators of component “Access to Advanced Education” (Scree plot of eigenvalues)



**Table 4** List of cluster categories with the underlying four-digit NACE industry classifications. Source: Adapted from: Ketels and Protsiv (2021)

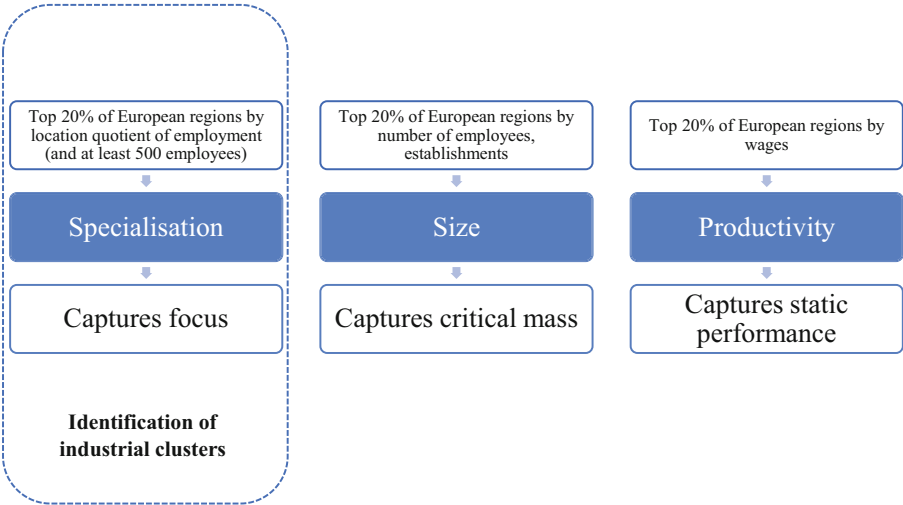
Cluster category	NACE Codes
Aerospace Vehicles and Defense	30.30
Agricultural Inputs and Services	01.61; 01.62; 01.63; 01.64; 20.15
Apparel	14.11; 14.12; 14.13; 14.14; 14.19; 14.20
Appliances	27.51; 27.52
Automotive	24.53; 24.54; 28.13; 29.10; 29.20; 29.31; 29.32; 30.40
Biopharmaceuticals	21.10; 21.20
Business Services	49.32; 62.01; 62.02; 62.03; 62.09; 63.11; 64.20; 70.10; 70.22; 71.11; 71.12; 71.20; 74.30; 74.90; 77.12; 77.40; 78.10; 78.30; 81.10; 82.20; 82.30
Coal Mining	05.10; 05.20; 09.90
Communications Equipment and Services	26.30; 61.20; 61.30; 61.90
Construction Products and Services	23.14; 23.51; 23.52; 23.61; 23.62; 23.64; 23.65; 23.70; 23.99; 24.20; 25.30; 35.30; 42.12; 42.22; 42.91
Distribution and Electronic Commerce	46.11; 46.12; 46.13; 46.14; 46.15; 46.16; 46.17; 46.18; 46.19; 46.21; 46.22; 46.23; 46.24; 46.31; 46.32; 46.34; 46.35; 46.38; 46.41; 46.42; 46.43; 46.44; 46.45; 46.46; 46.47; 46.48; 46.49; 46.51; 46.52; 46.61; 46.62; 46.63; 46.64; 46.65; 46.66; 46.69; 47.91; 52.10; 77.31; 77.32; 77.33; 77.34; 77.35; 77.39; 82.92
Downstream Chemical Products	20.12; 20.30; 20.41; 20.42; 20.51; 20.52; 20.53; 20.59
Downstream Metal Products	25.29; 25.40; 25.71; 25.72; 25.91; 25.92; 25.99
Education and Knowledge Creation	72.11; 72.19; 72.20; 85.41; 85.42; 85.52; 85.59; 85.60; 94.12
Electric Power Generation and Transmission	35.11; 35.12
Environmental Services	36.00; 38.12; 38.22; 38.32
Financial Services	64.11; 64.30; 64.91; 64.92; 64.99; 66.11; 66.12; 66.19; 66.30
Fishing and Fishing Products	03.11; 03.12; 10.20

**Table 4** (Continued)

Cluster category	NACE Codes
Food Processing and Manufacturing	10.31; 10.32; 10.39; 10.41; 10.42; 10.51; 10.52; 10.61; 10.62; 10.72; 10.73; 10.81; 10.82; 10.83; 10.84; 10.85; 10.86; 10.89; 10.91; 10.92; 11.01; 11.02; 11.03; 11.04; 11.05; 11.06; 11.07
Footwear	15.20; 15.11
Forestry	02.10; 02.20; 02.30; 02.40
Furniture	31.01; 31.02; 31.03; 31.09
Hospitality and Tourism	01.70; 55.10; 55.20; 55.30; 55.90; 77.21; 79.11; 79.12; 79.90; 91.02; 91.03; 91.04; 92.00; 93.11; 93.12; 93.19; 93.21; 93.29
Information Technology and Analytical Instruments	26.11; 26.12; 26.20; 26.40; 26.51; 26.52; 26.80; 58.21; 58.29; 26.70
Insurance Services	65.11; 65.12; 65.20; 66.21; 66.29
Jewelry and Precious Metals	32.11; 32.12; 32.13
Leather and Related Products	15.12
Lighting and Electrical Equipment	27.11; 27.12; 27.20; 27.31; 27.32; 27.33; 27.40; 27.90
Livestock Processing	10.11; 10.12; 10.13
Marketing, Design, and Publishing	58.11; 58.12; 58.14; 58.19; 63.12; 63.91; 63.99; 70.21; 73.11; 73.12; 73.20; 74.10; 91.01
Medical Devices	26.60; 32.50
Metal Mining	07.10; 07.21; 07.29
Metalworking Technology	23.91; 25.11; 25.61; 25.62; 25.73; 25.94; 28.41; 28.91; 25.12
Music and Sound Recording	59.20
Non-metal Mining	08.11; 08.12; 08.91; 08.92; 08.93; 08.99
Oil and Gas Production and Transportation	06.10; 06.20; 09.10; 19.10; 19.20; 49.50

**Table 4** (Continued)

Cluster category	NACE Codes
Paper and Packaging	17.11; 17.12; 17.21; 17.22; 17.23; 17.24; 17.29
Performing Arts	90.01; 90.02; 90.03; 90.04
Plastics	20.16; 22.21; 22.22; 22.23; 22.29; 28.96
Printing Services	18.11; 18.12; 18.13; 18.14
Production Technology and Heavy Machinery	25.21; 28.11; 28.12; 28.14; 28.15; 28.21; 28.22; 28.24; 28.25; 28.29; 28.30; 28.49; 28.92; 28.93; 28.94; 28.95; 28.99; 30.20; 30.99
Recreational and Small Electric Goods	28.23; 30.91; 30.92; 32.20; 32.30; 32.40; 32.91; 32.99
Textile Manufacturing	13.10; 13.20; 13.30; 13.91; 13.92; 13.93; 13.94; 13.95; 13.96; 13.99; 14.31; 14.39; 20.60
Tobacco	12.00
Transportation and Logistics	33.16; 51.10; 49.39; 49.41; 51.21; 51.22; 52.21; 52.23; 52.24; 52.29
Upstream Chemical Products	20.11; 20.13; 20.14; 20.17; 20.20
Upstream Metal Manufacturing	24.10; 24.31; 24.32; 24.33; 24.34; 24.41; 24.42; 24.43; 24.44; 24.45; 24.46; 24.51; 24.52; 25.50; 25.93
Video Production and Distribution	18.20; 59.11; 59.12; 59.13
Vulcanized and Fired Materials	22.11; 22.19; 23.11; 23.12; 23.13; 23.19; 23.20; 23.31; 23.32; 23.41; 23.43; 23.44; 23.49
Water Transportation	30.11; 30.12; 33.15; 50.10; 38.31; 50.20; 50.30; 50.40; 52.22
Wood Products	16.10; 16.21; 16.22; 16.23; 16.24; 16.29



**Fig. 16** Measurement of industrial clusters and their strength. (Adapted from Ketels and Protsiv 2016)



**Table 5** Descriptive Statistics of all variables

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
SPI	Multidimensional and output-oriented index for objective well-being	1111	68.747	4.742	50.448	79.612
GDPpc_In	Gross domestic product per capita (logarithm)	1111	10.244	0.399	8.868	11.145
Number industrial clusters	Number of different industrial clusters (i.e. LQ of cluster category belongs to the top 20% in all European regions and at least 500 employees in corresponding cluster category)	799	8.781	3.547	2	25
Strength industrial clusters	Ratio of 'performance stars' (i.e. industrial cluster belongs to top 20% in terms of number of employees and establishments [for size] and to top 20% in terms of wages [for productivity]) to the number of different industry clusters	799	2.914	1.172	1	6
Regional Inventor's Share	Weighted number of patents based on the share of inventors	1111	306.756	469.853	0.625	3577.992
Number Technological Specializations	Number of technological specializations (on four-digit CPC level)	1111	191.155	61.34	16	352
Inv_HHI	Inverse Herfindahl-Hirschman Index based on inventor-based activities in 35 technology fields classified by Schmoch (2008)	1111	0.9	0.073	0.32	0.959
Economic Active Population Share	Economic activity rates (in %) from 15 to 74 years in age	1111	65.426	5.05	41.8	76
Age of Population	Average age of the population in each NUTS-2 region	1111	43.097	3	35.4	51.5
Diverse Industry Structure	Number of different traded industries (based on employment data)	799	49.645	1.407	43	51
PopDens_In	Population density (logarithm)	1111	5.356	1.007	2.526	8.919

**Table 6** Pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) SPI	1.000	—	—	—	—	—	—	—	—	—	—
(2) GDPpc_In	0.739***	1.000	—	—	—	—	—	—	—	—	—
(3) Number industrial clusters	-0.271***	-0.265***	1.000	—	—	—	—	—	—	—	—
(4) Strength industrial clusters	-0.095***	0.050	0.185***	1.000	—	—	—	—	—	—	—
(5) Regional Inventor's Share	0.242***	0.464***	0.074**	0.220***	1.000	—	—	—	—	—	—
(6) Number Technological Specializations	0.400***	0.555***	-0.040	0.208***	0.460***	1.000	—	—	—	—	—
(7) Inv_HHI	0.134***	0.295***	0.022	0.151***	0.265***	0.641***	1.000	—	—	—	—
(8) Economic Active Population Share	0.698***	0.515***	-0.005	-0.025	0.286***	0.342***	0.071**	1.000	—	—	—
(9) Age of Population	0.087***	0.138***	-0.155***	-0.028	0.039	0.210***	0.078***	0.067**	1.000	—	—
(10) Diverse Industry Structure	-0.111***	-0.063*	0.153***	0.237***	0.218***	0.189***	0.106***	-0.053	0.055	1.000	—
(11) PopDens_In	0.283***	0.467***	0.044	0.126***	0.291***	0.404***	0.364***	0.224***	-0.305***	0.091**	1.000

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Table 7** Tests for reverse causality

	GDPpc_In	Number industrial clusters	Strength industrial clusters
	(1)	(2)	(3)
SPI	0.003 (0.003)	0.062 (0.104)	-0.032* (0.019)
GDPpc_In	0.811*** (0.044)	3.446*** (1.161)	0.175 (0.208)
Number industrial clusters	—	0.641*** (0.050)	—
Strength industrial clusters	—	—	0.722*** (0.048)
Regional Inventor's Share	0.00003*** (0.00001)	0.001 (0.001)	0.0001* (0.0001)
Number Technological Specializations	-0.0001 (0.0002)	0.007 (0.005)	0.001 (0.001)
Inv_HHI	0.063 (0.060)	0.897 (1.786)	-0.384 (0.429)
Economic Active Population Share	0.002 (0.002)	-0.031 (0.082)	0.007 (0.014)
Age of Population	0.001 (0.002)	-0.003 (0.053)	-0.001 (0.009)
Diverse Industry Structure	-0.007 (0.005)	0.122 (0.117)	-0.031* (0.018)
PopDens_In	0.021 (0.007)	-0.454** (0.187)	0.024 (0.026)
Constant	1.823*** (0.512)	-41.616*** (11.413)	1.988 (1.813)
Time-fixed effects	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	705	552	552
AR(1)— <i>p</i> value	0.000	0.000	0.000
AR(2)— <i>p</i> value	0.225	0.450	0.098
Hansen test— <i>p</i> value	0.227	0.905	0.297

Note: Two-step robust standard errors (GMM) in parentheses. A one-year time lag is applied for all independent variables

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 8** Test for non-linear effect of GDPpc\_ln

	SPI (1)
SPI	0.380*** (0.074)
GDPpc_ln	4.390 (24.181)
GDPpc_ln <sup>2</sup>	−0.081 (1.178)
Regional Inventor's Share	0.00002 (0.0002)
Number Technological Specializations	0.001 (0.004)
Inv_HHI	−1.549 (1.187)
Economic Active Population Share	0.090* (0.053)
Age of Population	0.109*** (0.037)
Diverse Industry Structure	0.00001 (0.076)
PopDens_ln	0.075 (0.168)
Constant	−3.966 (123.931)
Time-fixed effects	Yes
Region-fixed effects	Yes
Country-fixed effects	Yes
Observations	705
AR(1)— <i>p</i> value	0.000
AR(2)— <i>p</i> value	0.310
Hansen test— <i>p</i> value	0.291

Note: Two-step robust standard errors (GMM) in parentheses. A one-year time lag is applied for all independent variables

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

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