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Complexity and smart specialization: Comparing and evaluating knowledge complexity measures for European city-regions

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ABSTRACT

Recent work in economic geography posits that regional diversification into related and complex knowledge fields boosts innovative output and economic development. While the theoretical arguments on the importance of complex knowledge creation for regional development are widely accepted and scholars have started using measures of knowledge complexity to inform policy decisions in the context of the EU's smart specialization programme, the application of the theoretical concept to regional development policy raises a number of questions: First, what concept of knowledge complexity should be employed for policy analysis? Second, how is complexity operationalized empirically? Third, which alternative empirical operationalization of knowledge complexity should be used for policy purposes? This paper offers the first systematic comparison of three theoretically sound measures of knowledge complexity and related 48 empirical operationalizations of those three complexity indices based on regional patent data from 1996-2017 for a consistent set of 197 European metropolitan regions. The results show that the choice of complexity measure and emprical operationalization produces widely varying results and that more theoretical and conceptual work on knowledge complexity is required before it can be employed widely for policy purposes, and in particular, to inform smart specialization policies.

Keywords: Knowledge complexity; economic complexity index; economic fitness complexity index; structural diversity index; smart specialization policies;

INTRODUCTION

Smart specialization policies have played a critical role in the EU's Europe 2020 strategy built around smart, sustainable and inclusive growth (Balland and Rigby, 2017; Balland and Boschma, 2019a; Balland *et al.*, 2019; Rigby *et al.*, 2022) and will continue to play an important guiding role for funding allocation in the next EU funding cycle (2021-2027) in the form of the "Smart Specialization Strategies for Sustainability (S4)" (Smart Specialisation Platform, accessed 29.07.22). Smart specialization strategies refer to "the capacity of an economic system (a region for example) to generate new specialities through the discovery of new domains of opportunity and the local concentration and agglomeration of resources and competences in these domains" (Foray, 2014, p. 1). Focusing and building on region-specific capabilities addresses two major weaknesses of the European economy, national level fragmentation of public research systems and duplication of knowledge bases (Foray, 2014; Hassink and Gong, 2019).

The fuzziness of the concept of smart specialization caused problems for actors to implement smart specialization policies in the early phases (McCann and Ortega-Argilés, 2015; Capello and Kroll, 2016; Hassink and Gong, 2019), made it difficult for researchers and consultants to identify the direction of diversification in a systemic way as well as to evaluate the success or failure of smart specialization policies beyond anecdotal evidence (Balland and Rigby, 2017; Balland and Boschma, 2019b; Balland *et al.*, 2019; Trippl *et al.*, 2020; Rigby *et al.*, 2022). In order to reduce the complexity of real world cases to a manageable number of indicators linking a region's capabilities with promising potential diversification strategies, Balland et al. (2019) combine the concept of "relatedness" (Frenken *et al.*, 2007; Hausmann *et al.*, 2007; Hidalgo *et al.*, 2007; Hidalgo and Hausmann, 2009; Neffke *et al.*, 2011; Boschma *et al.*, 2013, 2015; Rigby, 2015; Essletzbichler, 2015; Boschma, 2017; Kogler *et al.*, 2017) with the concept of "complexity" (Fleming and Sorenson, 2001; Hidalgo and Hausmann, 2009; Tacchella *et al.*, 2012; Balland and Rigby, 2017; Broekel, 2019; Balland *et al.*, 2020; Mewes and Broekel, 2020; Hidalgo, 2021; Pintar and Scherngell, 2021). As the policy focus and the large majority of work in economic geography is on the role of technological change for (smart) economic growth, we restrict our analysis to knowledge complexity (Foray, 2014; Rigby, 2015; Kogler *et al.*, 2017;

Balland and Boschma, 2019b; Balland *et al.*, 2019; Pintar and Scherngell, 2021; Rigby *et al.*, 2022).

According to Balland et al. (2019), a smart specialization strategy is one of “related” diversification into complex knowledge domains because this strategy is supposed to lower investment risk and yield high benefits. The strategy is considered low risk, because the relatedness of new technologies to the existing regional technological portfolio reduces the risk of failure (loss of investment in new technology creation) (Rigby, 2015; Kogler *et al.*, 2017), generates higher localized spillover rates between firms and research institutions and thus, higher expected regional productivity and growth in “smart” regions (Jaffe *et al.*, 1993; Maskell and Malmberg, 1999). The strategy is supposed to generate medium- to long run benefits as complex knowledge is more difficult to imitate such that companies can extract monopoly rents for an extended period of time. The diversification into complex knowledge domain is the source of (technological) “strong competition” not easily eroded by (price) “weak competition” (Walker and Storper, 1989), setting regions on robust paths of economic development. While the theoretical arguments linking smart specialization to relatedness and complexity are sound and researchers seem to converge on a common standard to measure relatedness, a number of competing measures of knowledge complexity are proposed in the literature (Hidalgo and Hausmann, 2009; Tacchella *et al.*, 2012; Broekel, 2019). Hence, if knowledge complexity is identified as a key variable to inform public funding decisions, then it is important to know if different complexity measures lead to similar (ideally identical) policy conclusions. Otherwise, more work is required to determine the conceptual merits of different knowledge complexity measures supposed to inform policies backed by 67 billion EUR during the 2014-2020 funding cycle (Gomez Prieto *et al.*, 2019; Deegan *et al.*, 2021).

In order to address this concern, the paper offers a first systematic comparison of three different knowledge complexity measures based on Hidalgo and Hausmann (2009), Tacchella et al. (2012) and Broekel (2019) to evaluate patenting activity in a consistent set of 197 European metropolitan regions over the period 1996-2017[1]. The empirical operationalization

[1] While Broekel (2017) compared the technological complexity index based on the Hidalgo and Hausmann (2009) approach with the newly introduced structural diversity index (SDI) this paper focuses on regional knowledge

of knowledge complexity requires researchers to make choices on a number of key parameters (technology classification; rules for establishing substantive presence of technology classes in a region; regional allocation of knowledge production according to fractional or full patent count) that result in 48 different complexity values for each metropolitan region and for each year (see Figure 1). As all of those 48 measures can be justified on theoretical and conceptual grounds, we examine empirically the stability of measures over time, the consistency of results between measures, and the relationship of these measures to regional medium to long-term technological and economic change. The results should aid researchers and policy makers in their choice of complexity measures and illustrate that the implementation choices made have non-trivial consequences for regional complexity rankings and potentially, the development of smart specialization policies.

The paper is structured as follows. The next section reviews briefly the three complexity measures and discusses their operationalization. The third section introduces the dataset and sample on which the comparative analysis is based. Then, the fourth section summarizes the key choices to be made to calculate empirically regional knowledge complexity. Section five evaluates empirically the alternative complexity 48 different alternatives of calculating regional complexity values and the sixth section concludes the paper.

CONCEPTUAL FOUNDATION AND MEASURES OF KNOWLEDGE COMPLEXITY

Regional diversification into new specializations is smart if additional knowledge is added to the regional portfolio and if this knowledge is of qualitatively high value. Knowledge is of high value if it is tacit, i.e. difficult to codify, imitate and transfer between people and places (Polanyi, 1958, 1966; Kogut and Zander, 1992; Nonaka and Takeuchi, 1995; Lawson and Lorenz, 1999; Maskell and Malmberg, 1999; Asheim and Gertler, 2005). Complexity is a critical

complexity. The recent set of working papers by Nomaler and Verspagen (2022b, 2022a) also compare popular (knowledge) complexity measures and introduce their own alternative measure, and while they focus on the predictive capabilities of the differing approaches and establish a "supervised (machine) learning" algorithm (in contrast to the "unsupervised" approaches we highlight), the main conclusions they draw from their work are in line with ours.

component of tacit knowledge (Kogut and Zander, 1993). In turn, the creation of complex knowledge forms an integral component of smart specialization policies (Balland and Rigby, 2017; Deegan *et al.*, 2021; Rigby *et al.*, 2022).

Simon (1962) argues that complexity is a function of the number of components and the interdependence of these components. It requires information about the distinguishable components (component diversity) that make up a new technology or product as well as the difficulty of combining those original components (component linkage structure). The two defining characteristics, component linkage structure and component diversity offer two entry points into developing empirical complexity measures. Following the first path, Fleming and Sorenson (2001) focus on links between components to develop a technology complexity measure. Empirically, they derive the complexity of a patent by measuring the difficulty of combining different technology subclasses on patents. Following the second path, Hidalgo and Hausmann (2009) in their analysis of countries' commodity export baskets, offer a complexity measure "that reflects the difficulty of mastering the capabilities required to export a particular commodity (indexed by the rarity of exports of a given type), the diversity of capabilities held by different countries and the relatedness between them" (Balland *et al.*, 2019, p. 1257).

These two general approaches to measure complexity have been applied and modified to measure knowledge complexity: First, following Fleming and Sorenson (2001) and their focus on the component linkage structure, Broekel (2019) developed the structural diversity measure (SDI) that in turn is based on Emmert-Streib and Dehmer (2012). Second, following the "component diversity route", Balland and Rigby (2017) develop a knowledge complexity index based on Hidalgo and Hausmann's economic complexity index (ECI) (2009) while Tacchella et al. (2012) provide a modification of the ECI, the nonlinear, economic fitness complexity index of (EFC).

The economic complexity index (ECI) and economic fitness complexity index (EFC)

The ECI and EFC are based on the assumption that complexity is given by the properties of geographical ubiquity and technological (product) diversity. Technologies that are less ubiquitous, i.e. produced in a smaller number of locations are expected to be more complex, locations (cities, regions, states) that produce a large diversity of technologies are seen as more technologically advanced, able to produce complex (as well as less complex) technology. Applying the "method of reflections" (Hidalgo and Hausmann, 2009), an iterative process where information on technological ubiquity is used to calculate locational diversity and information on locational diversity is used to calculate technological ubiquity, produces a set of ECIs for each location and technology. Locations that produce a relatively large number of rare technologies exhibit a relatively high ECI (Balland and Rigby, 2017; Pintar and Scherngell, 2021; Rigby *et al.*, 2022). The formal presentation of the two complexity measures ECI and EFC follows next.

At the center of both measures is the location-by-knowledge-field matrix M_{ik}, representing the portfolio of knowledge production of all locations as it connects each location $i = (1 \dots N)$ with the knowledge field (activity) $k = (1 \dots K)$ in which it is specialized in. In network science jargon, *M* forms a bipartite network with two separate sets of nodes (*N* and *K*) where only nodes from different sets can be linked. Location *i* is connected to knowledge field *k* in the knowledge production network if, and only if, $M_{ik} > 0$. Further, location *i* is considered to be specialized in knowledge field *k* when $M_{ik} \geq 1$. Notice that M_{ik}can include discrete values (1 if a location *i* is specialized in a certain knowledge field *k* and 0 otherwise) or continuous values.

The location-by-knowledge-field matrix M_{ik} is the sole input for the ECI and the EFC. The *diversity* in knowledge production of location *i*, d_i^0, is given simply by the number of specializations of location *i* in knowledge fields *k.* From a network science perspective, it is equal to the degree centrality of node *i* in network *M*. *Ubiquity* of knowledge field *k*, u_k^0 is understood as the number of locations which are specialized in *k*, or as the degree centrality of node *k* in network *M*. The "method of reflections" introduced by Hidalgo and Hausmann (2009) takes the matrix *M* as input and produces estimates of ECI for locations and activities. This is done via a self-referential algorithm (1) that iteratively refines diversity and ubiquity measures to approximate location and activity complexity $(d_i^n; u_k^n)$ where *n* refers to the number of iterations:

$$\begin{cases} d_i^n = \dfrac{1}{d_i^0} \sum_k M_{ik} u_k^{(n-1)} \\ u_k^n = \dfrac{1}{u_k^0} \sum_i M_{ik} d_i^{(n-1)} \end{cases} \tag{1}$$

This algorithm yields generalized measures of diversity and ubiquity where each iteration builds on information from previous iterations. In our application to geographical knowledge production, each even iteration of d_i^n produces an estimate of locational knowledge complexity as the average of (generalized) ubiquity of knowledge fields location *i* is specialized in. Conversely, each uneven iteration of u_k^n yields an estimate of knowledge field complexity as the average (generalized) diversity of regions that specialize in knowledge field *k*.[2]

Caldarelli et al. (2012) established a reformulation of the "method of reflections" as a fixpoint problem that does not need to be solved iteratively but can be solved analytically. Again, matrix *M* enters as the sole input. Location complexity is approximated by the eigenvector $\widetilde{m}^{[2]}$ associated with the second largest eigenvalue of matrix $\widetilde{M} = \widehat{M}\ \widehat{M}'$. Here, the location-by-knowledge-field matrix *M* and its transpose is row-standardized to produce $\widehat{M}$ and $\widehat{M}'$. The location-location row-stochastic square matrix $\widetilde{M}$ is populated with estimates of weighted similarities between locations based on their (common) knowledge production activities. In line with most recent studies, we adopt this approach and define the ECI of locations as equal to $\widetilde{m}^{[2]}$.[3]

[2] In cases that *M* is not discretized to only signal specializations (e.g. when we measure specialization with the NRCA method, see Section0) but is populated by real values, the algorithms uses the full information of the knowledge production network, including information about the degree of specialization. For further details on the derivation and interpretation of the "method of reflections" see (Hidalgo and Hausmann, 2009; Caldarelli et al., 2012; Mariani et al., 2015; Balland and Rigby, 2017).

[3] The complexity of activities can be estimated reversing the order of matrix multiplication $\tilde{T} = \widehat{M}'\widehat{M}$ and calculating the eigenvector associated with the second largest eigenvalue of $\tilde{T}$, $\tilde{t}^{[2]}$.

Tacchella et al. (2012) raise conceptual and practical concerns with the Hidalgo and Hausmann (2009) method. While they agree with the idea that locational complexity can be represented through the diversity of "ubiquity-weighted" products they propose that "the complexity of a product cannot be defined as the average of the fitnesses of the countries producing it" (Tacchella *et al.*, 2012, p. 1) because only products produced by highly competitive countries contain information about the complexity of a product. Thus, they recommend a non-linear weighting of the complexity of the productive system of the producers (fitness) to determine the complexity of a particular product such that the complexity of a product produced by non-competitive countries is considered low while the complexity of products produced by competitive countries only is considered high. While a similar algorithm to the "method of reflections" is maintained, the non-linear weighting of countries determining product complexity differs from Hidalgo and Hausmann (2009) where countries enter with equal weights. Even though the EFC, as well as the ECI, was originally introduced with country level export data (Tacchella *et al.*, 2012; Cristelli *et al.*, 2015), recent work has utilized the index also in the context of geographical knowledge production.

The fitness complexity of location *i* and the activity complexity of *k* can be defined as follows (Tacchella *et al.*, 2012):

$$\begin{cases} \widetilde{F_i}^n = \sum_k M_{ik} Q_k^{(n-1)} \\ \widetilde{Q_k}^n = \dfrac{1}{\sum_i M_{ik} \frac{1}{F_i^n}} \end{cases} \qquad \begin{cases} F_i^n = \dfrac{\widetilde{F_i}^n}{\langle \widetilde{F_i}^n \rangle_i} \\ Q_k^n = \dfrac{\widetilde{Q_k}^n}{\langle \widetilde{Q_k}^n \rangle_k} \end{cases} \tag{2}$$

where $\langle \widetilde{F_i}^n \rangle_i$ refers to the arithmetic mean of fitness complexity values of all *N* locations and $\langle \widetilde{Q_k}^n \rangle_k$ accordingly to average complexity values of knowledge fields *K*. The algorithm starts with initial condition $Q_k^{\,0} = 1 \;\forall\, k$. Each iteration of $\widetilde{F_i}^n$is estimated as the sum of knowledge fields a location is specialized in, weighted by their complexity $Q_k^{\,(n-1)}$. The non-linear relationship between knowledge and location is introduced in the second equation. Here, the complexity of activity *k* is assumed to be inversely related to the number of locations that are able to specialize in it and locations are weighted by the inverse of their average fitness value. This assures that an activity is considered complex only if very few locations are specialized in it and if these locations have relatively high complexity scores. The fixed point of (2) yields estimates of locational fitness complexity and activity complexity.

The structural diversity index (SDI)

While the reliance on spatial ubiquity to determine knowledge complexity is reasonable it is not unproblematic as the geographic distribution of knowledge production can have many different explanations independent of knowledge complexity (e.g. institutional differences including innovation policies, cultural differences, attitudes towards entrepreneurship and risk-taking, etc.). Furthermore, it poses a potential endogeneity problem for spatial research and the choice of geographic units may influence the results (Broekel, 2019). Hence, Broekel (2019) suggests a different knowledge complexity measure extracted from the topological structure of knowledge networks and independent of the geographic distribution of knowledge production. The structural diversity index (SDI) developed by Broekel (2019) based on Fleming and Sorenson (2001), Hargadon (2003) and Emmert-Streib and Dehmer (2012) interprets technology as systems of interrelated components where the complexity of knowledge fields is determined by the complexity of the combinations of subcomponents that make up a knowledge field. This complexity of combinations is proxied by the structural diversity of the combinatorial network of subcomponents where structural diversity is understood as the diversity of network topologies a network contains (Emmert-Streib and Dehmer, 2012; Broekel, 2019). Networks comprised of different topologies require different amount of information to describe their structure (Broekel, 2019). For example, a simple star-like network can be fully described when the total number of nodes and the central node is known. Conversely, a so-called small-world network needs much more information to be fully defined as it may combine multiple different network topologies (e.g. stars, triangles, lattices).

For the development of the SDI , Broekel (2019) adapts from who developed the so-called network diversity score (NDS) index (Emmert-Streib and Dehmer, 2012) to distinguish “ordered”, “complex” and “random” networks. In this context, ordered networks represent the simplest, complex intermediate and random the most advanced networks in terms of their structure. The NDS is based on multiple network metrics that are combined in a way that was established using extensive numerical simulations to best distinguish the three types of network structures.

$$iNDS(G_k) = \frac{\alpha_{module}\, r_{motif}}{v_{module}\, v_\lambda} \qquad (3)$$

The individual network diversity score $iNDS(G_k)$ of the combinatorial network G_k is given by (3). The first term refers to the share of *modules*, $\alpha_{module} = \frac{\mathrm{M}}{V}$, with M being the number of modules and V equal to the number of nodes (vertices) of the network. Modules are small, densely connected subgraphs of a network and signal a certain organizational principle of said network. The variable r_{motif}[4] gives the ratio of the number of motifs of size three and four, $r_{motif} = \frac{motif(3)}{motif(4)}$. *Motifs* are small, connected subgraphs of a certain defined structure. The variables v_{module} and v_λ serve as a standardization and are interpreted like a coefficient of variation. Here, $v_{module} = \frac{var(m)}{mean(m)}$ approximates the variability in module sizes m and $v_\lambda = \frac{var(\Lambda(L))}{mean(\Lambda(L))}$ the variability of the Laplacian matrix L's eigenvalues $\Lambda(L)$.

As it may be the case that a network shows a structural diversity according to an ordered, complex or random network purely by chance, Emmert-Streib and Dehmer (2012) define the NDS for the whole population of networks G_{Pk} to which G_k belongs. While the population of networks is not observable, the NDS of G_{Pk} can be approximated by drawing independent samples *S* from G_k and taking the average of their *iNDS*.

$$NDS_k(\{G_k\}^S | G_{Pk}) = \frac{1}{S} \sum_{G_k \in\, G_{Pk}}^{S} iNDS(G_k) \qquad (4)$$

We follow Broekel (2019) in transforming the NDS for easier interpretation:

$$SDI_k = -1 \log(NDS_k) \qquad (5)$$

[4] For computational reasons, Broekel (2019) uses the ratio of graphlets of size three and four instead of r_{motif}.

Using this transformation, large values of SDI_k indicate random networks (complex knowledge fields), medium values complex networks (medium complex knowledge fields) and low values ordered network (low complex knowledge fields).

Because all those knowledge complexity measures are theoretically and methodologically sound and we do not have an "objective" benchmark to compare them with, a first step for comparing those measures and evaluating differences and similarities between them is their application to a particular empirical problem. We describe the sample and data we use for this comparison next.

DATA SOURCES AND SAMPLE CONSTRUCTION

It is important to note that "datasets are limited by the coarsening, frequency and universality of the administrative classifications and geographic boundaries to define them" (Hidalgo, 2021, p. 5). Researchers thus need to make a number of choices in the empirical operationalization including the geographic scale of analysis, the granularity of the technology/knowledge classification, the criteria for allocating knowledge packets (usually patents) to different knowledge classes, or "rules of presence" of technology/knowledge classes in particular locations. In addition to the choice of complexity measure, those decisions may or may not lead to different empirical measures of regional knowledge complexity and derived conclusions for smart specialization indices.

In line with existing literature, we proxy geographical knowledge production with patent data.[5] In particular, we use patent applications to the European Patent Office (EPO) filed by resident inventors of EU (incl. UK) and EFTA countries from 1996 to 2017. These patent applications are sourced from the OECD REGPAT[6] database, January 2021, which localizes

[5] Notwithstanding known limitations (see e.g. Pavitt, 1985; Griliches, 1990; Schmoch, 1999), patents include invaluable information about innovative activities.

[6] The OECD REGPAT database fully derives the EPO's Worldwide Statistical Patent Database (PATSTAT Global, Autumn 2020). It includes patent applications filed to the EPO and patent applications filed under the Patent Co-operation Treaty (PCT) at the international phase (see Maraut *et al.*, 2008 for details).

patents in NUTS-3 regions by inventor residence. We map these patents to metropolitan regions defined by EUROSTAT[7] (2019) which are expected to represent more accurately functional regions of knowledge creation. This is the case because they might reduce artificial intersections of urban agglomerations by NUTS-3 borders that could lead to problematic interpretations in a spatial context (Lepori *et al.*, 2019). In order gain a comparable set of metro-regions across the EU and EFTA countries, we (fractionally) remove patents where inventors are located outside of metropolitan regions. As the vast majority of knowledge production occurs in or around cities, the exclusion of peripheral regions removes around 20% of patents from the dataset.

Besides information about the inventor(s) and other relevant data, patent documents list the specific technology class(es) to which the invention pertains. The hierarchical classification system Cooperative Patent Classification (CPC) distinguishes between nine technologies at the highest level of aggregation (Sections) and about 250,000 classes at the most detailed level (Subgroups). The choice of level of disaggregation in terms of technology classes is an important one because it determines the level of detail in which technologies can be analyzed. Furthermore, if technology classes are too heterogeneous in size or cover sub-technologies within a class that are not homogenous enough, results based on these classes can be distorted if similar technology sub-fields are classified in different technology classes (Schmoch, 2008; Balland *et al.*, 2019). Recent related studies have mostly relied on the detailed 4-digit level (about 650 Subclasses) but also on the technological classification proposed by Schmoch (2008) which maps IPC[8] classes onto 35 technological fields (e.g. Antonelli *et al.*, 2017; Balland and Rigby, 2017; Balland *et al.*, 2019).

Following related literature (see e.g. Antonelli *et al.*, 2017; Broekel, 2019; Mewes and Broekel, 2020; Whittle *et al.*, 2020), we sum the number of patent applications for five consecutive

[7] Metropolitan regions are aggregations of NUTS-3 regions which are combined to more realistically represent urban regions and to come close to functional regions of cities, including commuter belts around those cities. NUTS-3 regions between urban agglomerations of at least 250.000 inhabitants are classified as periphery. We use metropolitan regions based on the NUTS 2013 classification. See https://ec.europa.eu/eurostat/web/metropolitan-regions/background for details.

[8] The International Patent Classification (IPC) is closely related to the CPC where the CPC is an extension of the IPC that is jointly managed and used by the EPO and the US Patent and Trademark Office. The IPC is used globally.

years to smooth out large fluctuations in annual patent applications for some city-regions. This procedure yields a dataset with yearly regional patent applications from 2000 to 2017 (where the focal year is at the end of the moving window)[9]. Prior to further refinements of the dataset that are necessary, specifically for the ECI and EFC index, this dataset contains 188,077 patent applications of inventors located in 269 city-regions in 2000 and 252,765 patents filed in 273 regions in 2017.

Despite the summation of patent applications over a five-year period, some city-regions produce few patents in a given period. These small numbers might bias some of our complexity measures (Cantwell and Vertova, 2004; Laursen, 2015). Hence, we set a fixed minimum threshold[10] of 50 patent applications per city-region and of 10 patent applications per technology for each period. This leads to the exclusion of between 72 city-regions in the early periods and 38 city-regions in 2017. City-regions that were excluded are predominantly Eastern and Southeastern European non-capital regions. This is not surprising as Eastern and Southern European regions have historically recorded very few patents (Fischer *et al.*, 2009). To make sure that changes in the annual sample of city-regions do not influence our results, we focus our analysis on the city-regions and technology classes that pass the minimum patent threshold in each period. 197 metropolitan regions and 542 (CPC 4-digit) technology classes fulfil these basic requirements every period. The final dataset contains 186,250 patent applications in 2000 and 247,321 patents applications in 2017 in 197 metropolitan regions and associated with 542/35 technology classes (CPC 4-digit / Schmoch).

In order to evaluate our complexity measures with regional outcome variables, we also utilize data on regional growth in GDP, GDP per employee and number of patents. GDP data is sourced from ARDECO[11].

[9] For example, the first period used is 2000, which consists of data of 1996,1997,1998,1999,2000.

[10] These thresholds are fractionally counted. Moreover, the exclusions are also fractionally, i.e., a patent is not completely removed from the dataset if its inventors are located in an excluded region and another region that remains in the dataset.

[11] ARDECO is the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy. This helpful database is a collection of regional data from different sources but mainly from EUROSTAT. See https://ec.europa.eu/knowledge4policy/territorial/ardeco-database_en. GDP is deflated to 2015 values. In order to make GDP data comparable to the metropolitan patent data, we translate NUTS 3 data

EMPIRICAL OPERATIONALIZATION OF COMPLEXITY INDICES

In order to calculate the three complexity indices for the 197 metropolitan regions, a number of decisions need to be made: First, researchers need to decide whether they aggregate individual patents to one of about 650 (in our case 542) 4-digit subclasses of the CPC (CPC-4) or one of the 35 technology fields identified by Schmoch (2008). In order to simplify we call CPC-4 subclasses and Schmoch technology fields, technology class. Second, as patents can be assigned to various technology classes and metropolitan regions (in case of multiple inventors) once researchers decided on their definition of technology class (Schmoch or CPC-4), they need to decide how patents are allocated across technology class and geographical units, either fractionally or through double (full) counting. In the case of fractional counting, a patent is allocated to each technology class assigned to it and each location where its inventors reside, where the total weight of a patent equals to one. In other words, each technology class – location of a patent receives the respective share of the sum of all technology class – locations to which a patent is assigned. Double counting, on the other hand, does not limit the weight of a patent to one but assigns a patent to all locations and technology classes listed on the patent. Third, once all patents are allocated to their respective technology classes and metropolitan regions, a "rule of significant presence", usually a measure of relative regional specialization in a particular technology class, needs to be established.

In this study we focus on four different metrics of specialization : the "revealed comparative advantage" (RCA, Balassa, 1965), the "normalized revealed comparative advantage" (NRCA, Yu *et al.*, 2009), the "relative specialization index" (RSI, Menzel and Maicher, 2017) and the "composite matrix" (CM, Fritz and Manduca, 2021).

In our application of regional knowledge production, all four metrics of specialization in question require as input a proxy of knowledge production of metropolitan region i in technology class k, X_{ik}.

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from ARDECO that comes in the NUTS 2016 classification first to NUTS 3 2013 classification and then aggregate this regional data to metropolitan regions.

The RCA is the most common alternative which is almost exclusively used in past studies of knowledge complexity. It approximates the relative specialization of a node of set *N* (a location *i*) in technology class *k*. This is done by comparing the share of locations' activity in technology class *k* with the share of *k* in the population as a whole.

$$RCA_{ik} = \frac{X_{ik}}{\sum_k X_{ik}} \Big/ \frac{\sum_i X_{ik}}{\sum_i \sum_k X_{ik}} \tag{6}$$

As the RCA is truncated on one side and its real value is hard to interpret, studies typically discretize the information generated by the RCA where a value larger than one signals a relative specialization of region *i* in technology class *k* and values below the cutoff-point the lack of specialization:

$$M_{ik}^{RCA} = \begin{cases} 1 \;\; if \;\; RCA_{ik} > 1 \\ 0 \;\; if \;\; RCA_{ik} \leq 1 \end{cases} \tag{7}$$

The composite matrix (CM) was introduced by Fritz and Manduca (2021) as an improvement of the RCA with specific properties of the ECI in mind. In addition to the relative specialization of location *i* in technology class *k* captured by the RCA, the CM adds information about the absolute amount of activity in a technology class.

$$M_{ik}^{CM} = \begin{cases} 1 \;\; if \;\; RCA_{ik} > 1 \; or \; X_{ik} > a_k \\ 0 \;\; if \;\; RCA_{ik} \leq 1 \; and \; X_{ik} \leq a_k \end{cases} \tag{8}$$

where a_k is a fixed cutoff-value that determines the specialization of location *i* in technology class *k* in addition to the relative information of the RCA. We set a_k equal to the 25th percentile of the distribution of patent activity in technology class *k*. This cutoff-point increases the density of the matrix *M* and corrects for a bias against larger locations of the original RCA (Fritz and Manduca, 2021).

The relative specialization index (RSI, Menzel and Maicher, 2017) is another variation of the basic idea of the RCA that exhibits a few notable properties. The RSI is bounded between -1 and 1 with 0 indicating average specialization, compared to the asymmetric range of the RCA between 0 and infinity with 1 indicating average specialization. As the right side of the distribution ($RSI > 0$) follows a bell-shaped curve it is possible to define the cutoff of specialization using the underlying empirical distribution of RSI values.

$$RSI_{ik} = \frac{X_{ik}}{\sum_k X_{ik}} - \frac{\sum_{j \neq i} X_{jk}}{\sum_{j \neq i} \sum_k X_{jk},} \tag{9}$$

with *j* being a location other than *i*. The interpretation of the RSI is similar to that of the RCA in that higher RSI values signal strength of association between location *i* and technology class *k*. However, the share of technology class *k* in location *i* is related to the share of technology class *k* in all locations (minus location *i*) which can make a difference in large regions. We follow Menzel and Maicher (2017) and define specialization as a RSI_{ik} value that exceeds a location-specific threshold:

$$M_{ik}^{RSI} = \begin{cases} 1 \;\; if \;\; RSI_{ik} > (0 + std_i) \\ 0 \;\; if \;\; RSI_{ik} \leq (0 + std_i) \end{cases} \tag{10}$$

where std_i equals the standard deviation of positive RSI_{ik} values in location *i*. In other words, location *i* is specialized in technology class *k* if location *i* patents sufficiently more in technology class *k* than in other technology classes.

In contrast to the other three versions to measure specialization, we do not need to discretize the normalized revealed comparative advantage index (NRCA), introduced by Yu et al. (2009) and hence, we can exploit the full information contained in the metric. Conceptionally, the NRCA is similar to the RCA where a theoretical comparative-advantage-neutral strength of association between location and activity is compared with the actual activity in technology class k in region *i* to estimate whether a specialization exists. From equation (6), we can rearrange and express the comparative-advantage-neutral (expected) number of patents of region *i* and technology class *k* as:

$$\hat{X}_{ik} = \frac{\sum_k X_{ik} \sum_i X_{ik}}{\sum_i \sum_k X_{ik}} \tag{11}$$

The difference between the actual number of patents of location *i* in technology class *k* and its expected value, $\hat{X}_{ik}$, can then be stated as:

$$\Delta X_{ik} = X_{ik} - \hat{X}_{ik} = X_{ik} - \frac{\sum_k X_{ik} \sum_i X_{ik}}{\sum_i \sum_k X_{ik}} \tag{12}$$

When normalizing ΔX_{ik} by the total number of patents, $\sum_i \sum_k X_{ik}$, the NRCA index follows:

$$NRCA_{ik} = \frac{\Delta X_{ik}}{\sum_i \sum_k X_{ik}} = \frac{X_{ik}}{\sum_i \sum_k X_{ik}} - \frac{\sum_k X_{ik} \; \sum_i X_{ik}}{\sum_i \sum_k X_{ik} \; \sum_i \sum_k X_{ik}} \qquad (13)$$

Hence, the NRCA measures the comparative advantage of location *i* in technology class *k* relative to the expected comparative advantage given the size of the location and the size of the technology class. The NRCA possesses a few helpful properties that the RCA lacks. First, the magnitude of relative comparative advantage can be directly interpreted where a NRCA value twice as large signals a comparative advantage of twice the expected comparative advantage. Second, the sum (and mean) of NRCA values of a location (across all technology classes) and the sum (and mean) of technology class NRCAs (across all locations) equal to zero. Consequently, if a region gains comparative advantage in one technology class, it must lose comparative advantage in other technology classes. This property fits well with the conceptual idea of comparative advantage (Yu *et al.*, 2009). Third, the NRCA is additive in terms of location and activity. This means that the measure of comparative advantage is not dependent on chosen classifications of locations and technologies as long as hierarchical classifications are used. For example, comparative advantage of a region in digital technologies equals the sum of the individual comparative advantages of the region in each (sub)technology that falls within digital technologies. This property is useful with regards to the topic and data used in this paper (e.g. complexity measures that vary only according to the Schmoch (2008) and CPC 4-digit classifications should be similar). Fourth, possible NRCA values range from $-¼$ to ¼ with zero being the neutral point of no specialization. This symmetry is a helpful property, especially if the NRCA values are to be used as further inputs for analyses (Yu *et al.*, 2009). Last, zero activity of a location in a given field does not result in a constant zero value of the NRCA as is the case with the RCA. In contrast, the amount of comparative disadvantage depends on the total number of patents in location *i* and technology class *k*. That means that a large region (in terms of total number of patent applications) has a larger comparative disadvantage compared to a smaller region if both do not produce any patents in a particular technology class *k*.

We transform NRCA so its possible values range between 0 and 2 with 1 being the comparative-advantage-neutral point. This does not change the beneficial properties of the NRCA index but makes values more tractable and allows us to use the results as the matrix *M*.

$$M_{ik}^{NRCA} = \frac{NRCA_{ik}}{1/4} + 1 \tag{14}$$

In the case of the ECI and EFC where information on the geographical distribution of knowledge classes influences the ECI and EFC directly, researchers need to decide on the method of "counting" ex ante. For the SDI, researchers only need to decide ex post how the knowledge complexity values calculated at the level of technology classes are distributed across geographical units. In this sense, the calculation of the SDI is independent of their spatial concentration, but, in order to calculate location specific SDIs, some form of geographical weighting scheme is required. To calculate the SDI with patent data and integrate it in our comparison of complexity indices, we require additional information. We mostly follow Broekel (2019) in the operationalization of the SDI. As the SDI builds on data of technology classes, (sub)components and their combinations need to be defined. For the technological level of CPC 4-digit classes, we closely follow Broekel (2019) and define the most detailed level of CPC classes (Subgroups) to represent components of CPC 4-digit classes. When analyzing patent data on the broad technological level introduced by Schmoch (2008), we take CPC 4-digit classes as (sub)components[12]. The SDI is based on the combinatorial network of technology classes. We observe these combinations empirically as co-occurrence of component technology classes on patent documents. The following steps are taken for each period t to create the combinatorial network G_k but we omit subscript t to improve readability.

For each focal technology class *k*, all patent documents are retrieved where at least one of the technology classes listed on the document corresponds to k[13]. Then, we calculate the co-

[12] The Schmoch classification is defined based on the International Patent Classification and not the CPC. However, the CPC is based on the IPC and identical in most cases at the 4-digit level.

[13] We exclude technology classes that are present on less than 10 patents. This is done to avoid further computational problems that might arise with such small networks and because technology classes that are apparently not used are of no particular interest for our analysis. Moreover, this is done in related literature (Broekel, 2017).

occurrences of component classes and create the adjacency matrix $\hat{A}_k$. As the NDS and consequently the SDI is not defined on valued networks (Emmert-Streib and Dehmer, 2012; Broekel, 2019), we dichotomize the matrix $\hat{A}_k$ to keep only information about the existence of a combination but not about its frequency. Now, the matrix $\hat{A}_k$ represents the combinatorial network $\tilde{G}_k$. It links all components that are combined on patents where the focal technology *k* is present. Note that this also includes combinations of component technology classes that are not part of *k* itself but are found on patent documents with *k*.

It is sometimes the case that $\tilde{G}_k$ is made of multiple non-connected network components. Because NDS requires connected networks, we only use the main component of $\tilde{G}_k$. As mentioned in Section 0, it is required to calculate structural diversity on multiple samples from $\tilde{G}_k$. We randomly draw $S = 50$[14] nodes $c \epsilon S$ from $\tilde{G}_k$ and create *S* sample networks $\tilde{G}_{k,c}$ using a random walktrap algorithm[15] that explores the network, starting from *c*. Finally, this combinatorial network $\tilde{G}_{k,c}$ is used to calculate $iNDS(G_k)$ in equation (3) which is averaged over all samples in equation (4) and transformed in equation (5) to yield the structural diversity index of technology class *k*.

As the SDI is in its estimation independent of the location of knowledge production, we need to weight technology class specific SDIs to obtain region-specific SDIs. There are multiple ways of calculating SDI values for metropolitan regions including the calculation of a weighted average of technological complexity values according to the number of patents per technology class in a region (Rigby *et al.*, 2022) or estimating regional knowledge production capabilities by calculating an average of only the top most complex patents a region has produced (Mewes and Broekel, 2020). In order to facilitate the comparability of the SDI to ECI and EFC, we opt

[14] In case the network has fewer than 50 nodes, *S* is set equal to the number of nodes of the network.

[15] Broekel (2019) uses a random walktrap algorithm with a constant 150 steps. In our estimations we observed that when taking a constant number of 150 steps, the random walker did not manage to sufficiently explore larger networks (Emmert-Streib and Dehmer, 2012). This led to the fact that there was no consistent positive correlation between the size of the sampled combinatorial network and the structural diversity when applying the SDI to generated small-world networks. However, this property should be inherent in the index, as Emmert-Streib and Dehmer (2012) showed. To remedy this, we used a relative number of steps equal to 50% of the number of nodes of the combinatorial network samples are drawn from. This enables the random walker to explore more nodes when the original network is larger and better contains information about the size of the network in the samples.

for estimating regional SDI as the (weighted) average structural diversity of technology classes *k* a region is specialized in. Conveniently, this information is already given by the four *M* matrices that are used in calculating the ECI and EFC.

Hence, we define SDI_i as the unweighted average of SDI_k of technology classes *k* in which metropolitan region *i* is specialized according to RCA, RSI and CM. When allocating regional SDI based on the relative specialization metric NRCA, we utilize the full information of the real-valued strength of association and calculate the weighted average of all technology classes SDI_k with the weight equal to element M_{ik}^{NRCA} to yield SDI_i.

Combining the three complexity measures, ECI, EFC and SDI, two technology classes (CPC-4 and Schmoch), two allocation methods (fractional or full counting) with four specialization indices (RCA, NRCA, RSI, CM) yields a total of 3*2*2*4=48 alternative knowledge complexity measures for each of the 197 metropolitan regions and 5-year periods (see Figure 1). Those 48 alternative measures of knowledge complexity are compared next.

Figure 1 The 48 variations of the regional knowledge complexity index

Complexity measure	Technology	Counting	Spec.	Var.	Comparable applications
Economic Complexity Index (ECI)	Schmoch	fractional	RCA	1	(Balland et al., 2019), (Whittle, 2019), (Pintar and Scherngell, 2021)
			NRCA	2	
			RSI	3	
			CM	4	
		double	RCA	5	
			NRCA	6	
			RSI	7	
			CM	8	
	CPC4	fractional	RCA	9	(Balland and Rigby, 2017), (Ivanova et al., 2017), (Rigby et al., 2019)
			NRCA	10	
			RSI	11	
			CM	12	
		double	RCA	13	(Antonelli et al., 2017), (Antonelli et al., 2020)
			NRCA	14	
			RSI	15	
			CM	16	
Economic Fitness Complexity Index (EFC)	Schmoch	fractional	RCA	17	
			NRCA	18	
			RSI	19	
			CM	20	
		double	RCA	21	
			NRCA	22	
			RSI	23	
			CM	24	
	CPC4	fractional	RCA	25	(Sbardella et al., 2018)*, (Napolitano et al., 2020)*, (Sbardella et al., 2021)**
			NRCA	26	
			RSI	27	
			CM	28	
		double	RCA	29	
			NRCA	30	
			RSI	31	
			CM	32	
Structural Diversity Index (SDI)[+]	Schmoch	fractional	RCA	33	
			NRCA	34	
			RSI	35	
			CM	36	
		double	RCA	37	
			NRCA	38	
			RSI	39	
			CM	40	
	CPC4	fractional	RCA	41	(Broekel, 2019), (Juhász et al., 2020), (Mewes and Broekel, 2020)
			NRCA	42	
			RSI	43	
			CM	44	
		double	RCA	45	
			NRCA	46	
			RSI	47	
			CM	48	

Sources: ECI: (Hidalgo and Hausmann, 2009), (Caldarelli et al., 2012); EFC: (Tacchella et al., 2012); SDI: (Broekel, 2019), (Emmert-Streib and Dehmer, 2012); Schmoch: (Schmoch, 2008); RCA: (Balassa, 1965); normalized revealed comparative advantage (NRCA): (Yu et al., 2009); relative specialisation index (RSI): (Menzel and Maicher, 2017); composite matrix (CM): (Fritz and Manduca, 2021).

Note: [+]In contrast to ECI and EFC, SDI is defined only on the technological level. Since we compare complexity measures in a policy context and on a regional level, we attribute SDI values to regions via a weighted average of the regions technological portfolio.*Papers focus on a subset of "green" technologies on different technological levels, are not directly comparable to CPC4. **This study uses CPC classes but not exclusively CPC4.

EMPIRICAL EVALUATION OF COMPLEXITY MEASURES

As there is no “true” complexity value to benchmark different complexity measures against (Hidalgo, 2021), it is important to examine how sensitive the geographical complexity measures are to their empirical operationalization.

We evaluate the 48 alternatives according to the following criteria:

I. In order to examine the consistency of regional complexity scores across the 48 alternatives we first calculate correlation coefficients between the annual complexity scores of the 197 metropolitan regions. The correlation coefficients are then averaged over time to produce a measure of consistency between regional complexity indices which we visualize with a correlation matrix (Figure 2) and examine via a simple modelling framework (Table 1). Furthermore, we illustrate the problem of different complexity values to inform smart specialization policies through an application of three alternative complexity measures for 35 knowledge fields for the metropolitan area of Vienna (Figure 3).

II. As diversification into new technologies is path-dependent and rooted in the existing set of capabilities (Martin and Sunley, 2006; Feldman and Kogler, 2010; Neffke *et al.*, 2011; Boschma *et al.*, 2015; Essletzbichler, 2015; Boschma, 2017), the measures should be relatively stable over time. Small annual changes in metropolitan complexity values and metropolitan rankings according to complexity values over time are expected, but a complete reshuffling or reversals in rankings from one year to another are implausible. We would interpret those temporal inconsistences as problematic as the diversification strategies of cities could be classified as smart in one year and non-smart in another. We visualize the problem with two bump charts to illustrate a case of relative stability and a case of relative instability of metropolitan complexity rankings over time (Figure 4a and 4b). We summarize the temporal consistency for all 48 alternatives by correlating metropolitan complexity scores in year t with those of year t+1 (Figure 5).

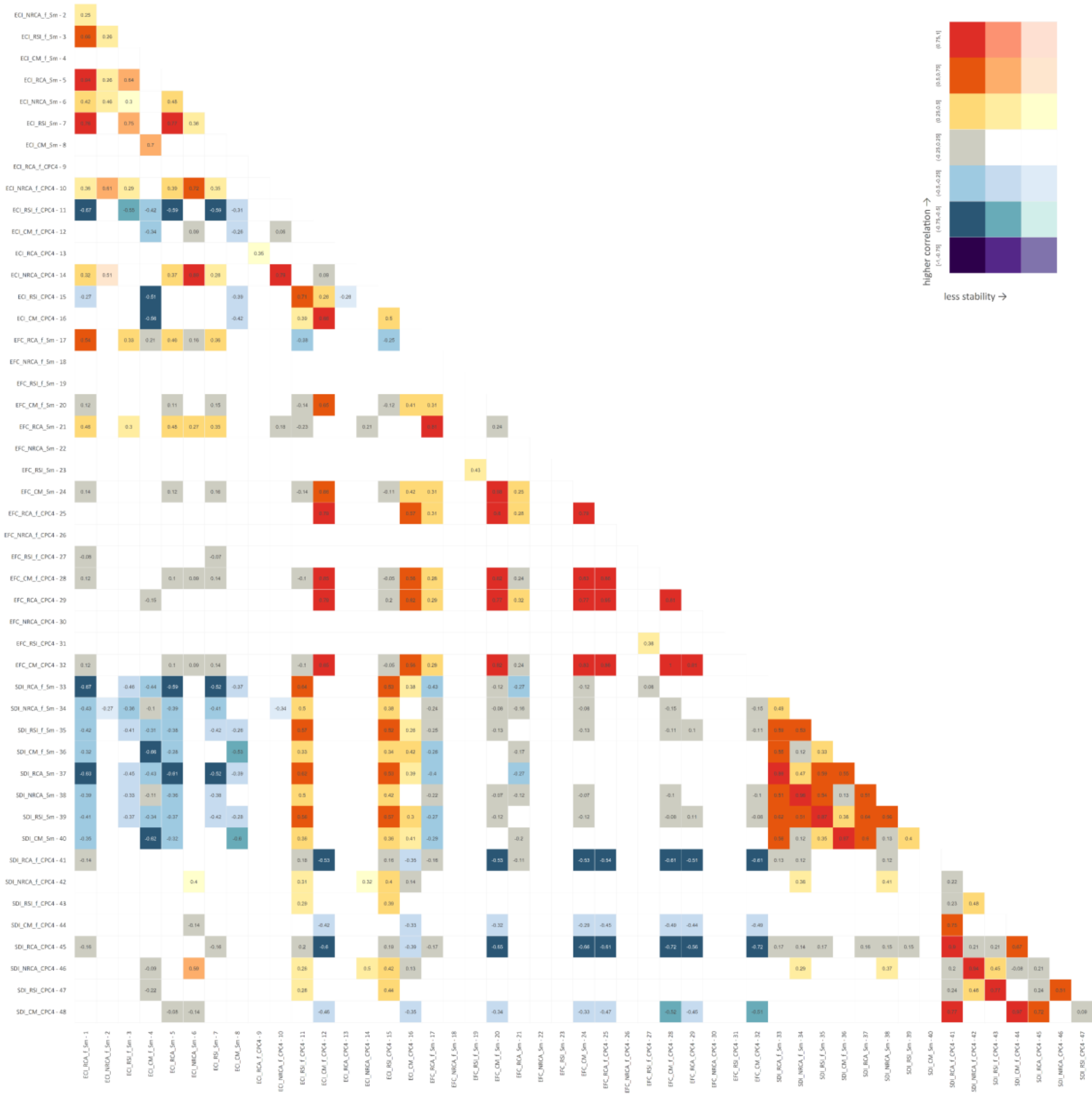
III. The literature suggests that knowledge complexity is linked to desirable economic outcomes such economic and technological development (Antonelli *et al.*, 2017, 2020; Mewes and Broekel, 2020; Pintar and Scherngell, 2021; Rigby *et al.*, 2022). We thus correlate the alternative complexity values with GDP and GDP/capita growth as well as the growth in the number of patents. As we would expect knowledge complexity to influence economic and technological growth over the medium to long-run we correlate the 15-year growth rates of those indicators with the complexity values at the base year.

I Relationship between complexity measures

Based on the theoretical and conceptual literature, we have little expectations on the relationship between the 48 different complexity measures. In order to get an idea about the relationship between our 48 complexity measures, Figure 2 depicts bivariate relations between the metropolitan regions' complexity scores according to those complexity measures. While some measures appear to yield similar rankings, others do not. Strong positive (and stable) relationships appear more common among the alternatives with the same complexity measure.

In the case of the ECI (top of the graph), positive correlation coefficients dominate when Schmoch is used as technology class. In the case of the EFC the use of technology class appears to be less important and positive correlations seem to be restricted to those alternatives that utilize the CM or RCA as specialization measure (although many of the correlation coefficients are not stable over time). In the case of the SDI, positive correlation coefficients are apparent if the same technology classification is used (either Schmoch or CPC-4) (bottom right corner). Furthermore, we observe strongly negative and stable correlation coefficients between the ECI (with Schmoch) and SDI (with Schmoch) as well as between EFC and SDI indices. But these are general trends from which individual pairs of correlation coefficients deviate.

Figure 2 Bivariate correlation coefficients between alternative complexity measures



Note: Cell values reflect the contemporaneous correlation between variations of the complexity index, averaged over all 18 periods. Cell color and shadings represent the strength of association as well as the variation over time where less stability (higher variation) is signaled by lighter colors. Correlations around zero that are also not stable are not labeled and filled with white. This is done for visualization purposes only.

In order to analyze systematically the factors that influence the bivariate relationship between two alternatives, we introduce a simple modelling framework. Table 1 presents the results of this modelling exercise where we explain the average bivariate correlation between two knowledge complexity indices with a set of dummy variables that indicate whether two alternatives share the same specifications in terms of the measure, technology classification, method of counting and metric of specialization used, or combinations thereof. For example, for alternatives 1 (ECI, Schmoch, fractional, RCA) and and 9 (ECI, CPC4, fractional, RCA) the dummy for measure=1, for technology (tech)=0, for counting (count)=1 and for specialization (spec)=1. The intercept is the average correlation coefficient if all dummies are equal to 0 (i.e. all specifications differ). Table 1 includes the results for all complexity measures jointly (columns 1 and 2) and for all the complexity measures separately (columns 3-8). We focus on the models including all complexity measures first. The negative and significant intercept (Model (1)) indicates that the complexity measures result in no relation or even negative relationships between metropolitan rankings based on those measures, suggesting that the choice of measure matters. Models (1) and (2) also indicate that the complexity measure is the most important variable to obtain a positive correlation between two alternative complexity measures.

Model (2) examines whether the effects of utilizing the same specification other than the measure on the bivariate correlation between alternatives is context dependent. This is done by introducing interaction terms. It turns out that applying the same technology classification or the same metric of specialization increases the bivariate correlation substantially[16] but only if the two alternatives apply the same complexity measure[17]. Interestingly, using the same complexity measure but varying all other variables (different technology classifications or specialization indices) does not raise the correlation coefficient. Hence, it appears that the measure of complexity <u>in conjunction with</u> common technology classifications or specialization indices is the most important indicator to generate positive correlation coefficients between two alternatives. We examine the relationship between alternatives for each of the three complexity measures separately next (columns 3-8).

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[16] Introducing interactions into the model complicates the interpretation of coefficients somewhat. The effect of having the same technology classification (given the same measure but different metric of specialization) on the bivariate correlation is equal to the sum of the coefficient of the "tech" dummy and the interaction term between "measure" and "tech" (-0.074 + 0.293 = 0.219). Respectively, the effect of using the same metric of specialization (given the same measure but different technology classification) is 0.223 (-0.032 + 0.255). Note, since the coefficient of the method of counting is basically zero in Model (1) and interaction terms with the dummy variable "count" were also zero, we have excluded dummy interaction terms with the method of counting from Model (2).

[17] The negative coefficient on the technology classification in Model (2) needs to be interpreted with caution. Because we have introduced interactions in the model, this coefficient refers to the decline in correlation between alternatives when they share the technology classification but differ in terms of measure and specialization.

Table 1 Regression output structural relations between knowledge complexity measures

	Full		ECI		EFC		SDI	
dep. var.: pearson cor. between variations	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(Intercept)	-0.040***	0.020	-0.053	-0.025	0.065	0.079	0.077**	0.101***
	(0.014)	(0.015)	(0.051)	(0.050)	(0.046)	(0.048)	(0.032)	(0.029)
measure	0.196***	0.004						
	(0.016)	(0.022)						
tech	0.027*	-0.074***	0.278***	0.187***	0.066	0.021	0.342***	0.260***
	(0.015)	(0.019)	(0.055)	(0.057)	(0.050)	(0.055)	(0.034)	(0.033)
count	-0.016	-0.004	-0.028	0.006	-0.018	0.001	-0.029	0.006
	(0.015)	(0.014)	(0.055)	(0.057)	(0.050)	(0.055)	(0.034)	(0.033)
spec	0.059***	-0.032	0.197***	-0.003	0.297***	0.204*	0.230***	0.065
	(0.017)	(0.025)	(0.069)	(0.111)	(0.063)	(0.107)	(0.043)	(0.065)
measure × tech		0.293***						
		(0.030)						
measure × spec		0.255***						
		(0.037)						
tech × spec		0.062*		0.534***		0.260*		0.471***
		(0.033)		(0.152)		(0.146)		(0.089)
count × spec				0.037		0.006		0.000
				(0.152)		(0.146)		(0.089)
Num.Obs.	1128	1128	120	120	120	120	120	120
R2 Adj.	0.128	0.218	0.195	0.272	0.148	0.161	0.495	0.605
AIC	24.7	-95.2	54.5	44.3	33.9	34.0	-57.7	-85.6

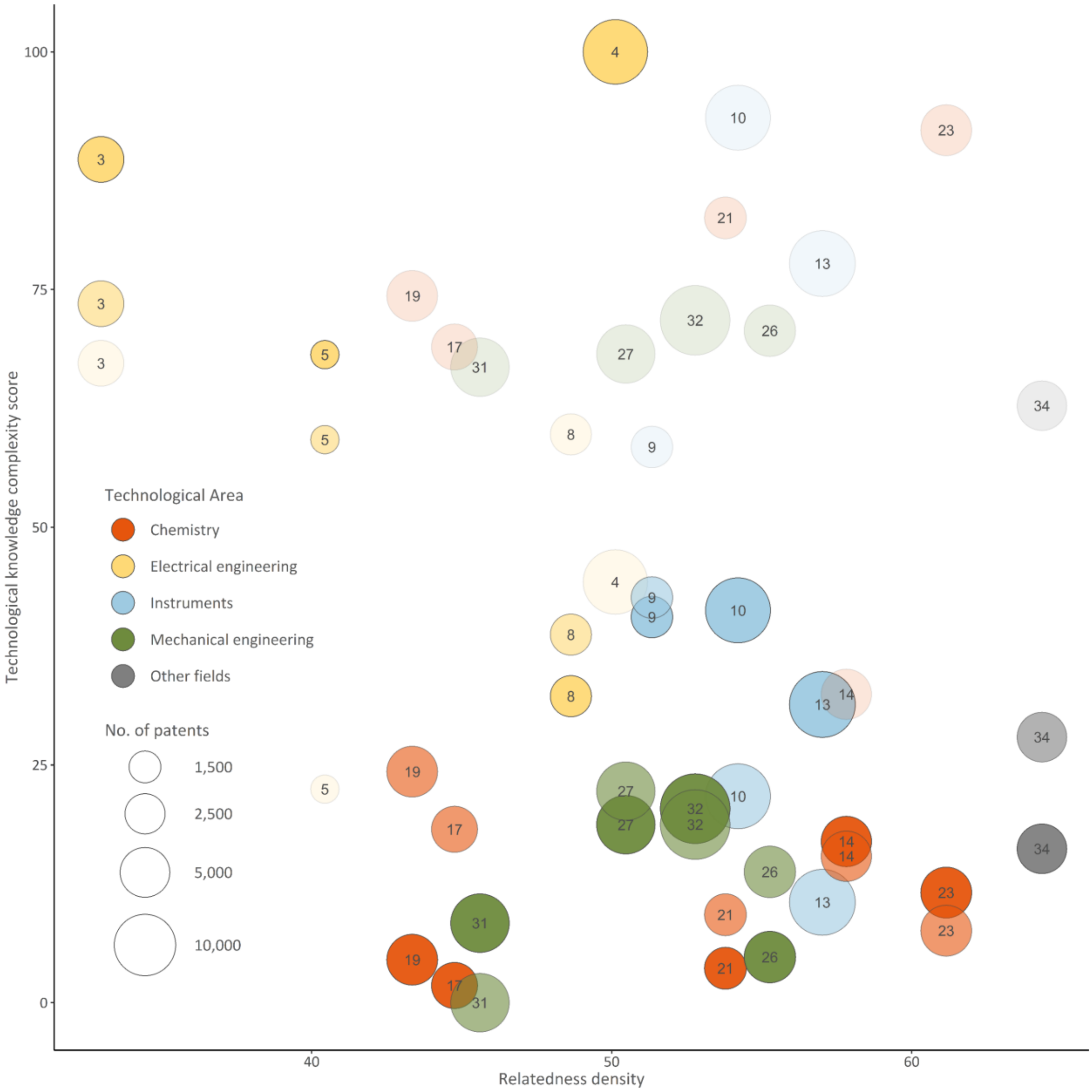
Note: Dependent variable is the contemporaneous pearson correlation between variations on the knowledge complexity index, averaged over all time periods. All models are estimated using OLS. Standard errors are shown in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01.

Comparing the results for the three complexity values individually with the general models (1) and (2), we find that the explanatory power (R2 Adj.) increases, even though we control for fewer variables. The results can be summarized as follows: First, inspection of the intercept reveals that a positive correlation in metropolitan regions' complexity scores where all variables differ (dummies set to 0) is found only for the SDI. Second, we find similar patterns for the ECI and SDI (Models (3),(4) and (7),(8)): (a) Using the same technology classification or specialization measure increases bivariate correlation substantially for ECI and SDI (Models (3) and (7)) without taking interaction effects into account; (b) Applying the same method of counting patents (fractional or full) has no impact on the correlation between two alternatives; (c) The interaction models (Models (4) and (8)) illustrate that specialization increases bivariate correlation between alternatives only if they also apply the same technology classification. Third, in the case of the EFC (Model 5) only using the same specialization metric significantly increases bivariate correlation between alternative complexity measures.

Overall, it appears that regional complexity scores vary substantially across alternative complexity measures. We illustrate the problem of these differences in complexity values for its application to inform a city's smart specialization strategy using the metropolitan region of Vienna. Balland and Rigby (2019) suggested the use of complexity values to inform smart specialization policies by arguing that cities should diversify into technologies that are related to the existing stock of technologies and that are complex. If all the alternative specifications to calculate the complexity of technologies yielded similar results, this exercise would be easy to implement and researchers would be free to use any of the complexity index specifications. In order to see if that is the case, we compare the technology complexity values of three alternatives (5, 21, 37) with varying complexity measures (ECI, EFC, SDI) but keeping all other variables constant (Schmoch, RCA, double counting). Although we could use CPC-4 or finer grained technology classifications for this kind of policy analysis, for illustrative purposes we use the 35 technology fields of Schmoch. Figure 3 plots the relatedness density (Balland *et al.*, 2019) and the three complexity values for all those technology fields in which Vienna is not specialized yet.

The relatedness values of the technology classes to the technology portfolio of Vienna are depicted on the horizontal axis, while the complexity values for the three alternatives (standardized by complexity measure between 0 and 100) are depicted on the vertical axis. The relatedness values are constant for each technology class, while the complexity values vary depending on whether ECI, EFC or SDI were used to calculate them. Although we keep most variables constant, the complexity values for some of the technologies vary substantially (e.g. Measurement (10) and Basic Materials (19)). Given that a smart specialization policy dictates that Vienna should diversify into related technologies (e.g. Other consumer goods (34) or chemical engineering (23)) we would then consult the complexity values of those technologies. It turns out that they are low when using the ECI or EFC but high when using the SDI to calculate the complexity values for those two technology fields. Hence, only in the case of the SDI would it be “smart” for Vienna to invest in those two technology fields. Policy recommendations based on the ECI would favor investment in Digital Technologies (4) even if investment in this technology field is somewhat more risky. Those differences in complexity values would be even more pronounced when choosing CPC-4 or different specialization measures and policy recommendations based on these measures as a result even more diverging. As these differences exist, are there any means of narrowing down the alternatives?

Figure 3 Relatedness density and selected complexity values for Vienna



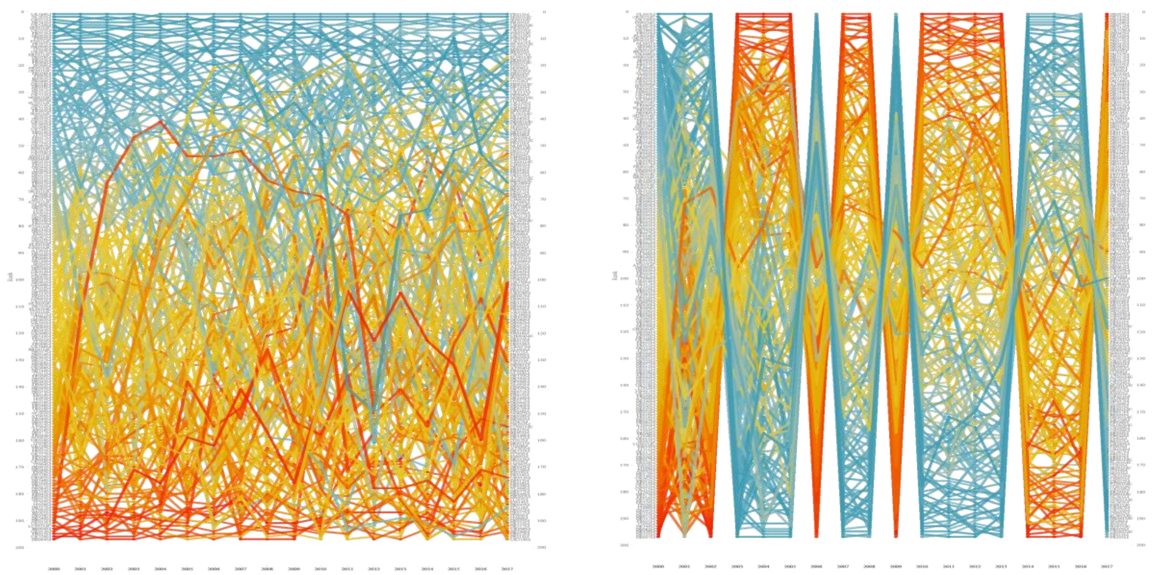
Note: The numbers in the circles refer to the technology field according to Schmoch (2008) where only technology fields are shown in which Vienna does not yet have a specialization. Colors are reserved for broad technology categories. The shading reflects the complexity measure. Dark shading = ECI; Medium shading = EFC; Light shading = SDI. All three measures apply Schmoch, double/full counting, RCA, and refer to the latest period (2017).

II Stability of metropolitan rankings over time

As argued above, one of the expectations for a complexity measure would be temporal stability. Because of the path-dependent nature of technological change, we would not expect complexity values for individual cities to change substantially from year to year. In order to see whether this is the case, Figure 4 plots the rankings of cities based on their complexity values (here illustrated for two alternatives) over time. Figure 4a displays a case of relative stability, while Figure 4b illustrates a case of extreme instability. Figure 4a includes the annual rankings of the 197 metropolitan areas for alternative 1 (ECI, Schmoch, fractional, RCA). While there is some movement of cities up and down the complexity ranking over the whole 18-year period, there is little movement in the rankings on a year-to-year basis. This result is plausible and in line with expectations. Figure 4b displays the annual metropolitan rankings for alternative 9 (ECI, CPC4, fractional, RCA). Although varying only the level of technology aggregation, this version is unstable in the context of EU metropolitan regions. Rankings are reversed frequently and this alternative thus seems unsuitable for analyzing knowledge complexity in the European context (see also Balland and Rigby, 2017; Rigby *et al.*, 2022).

Figure 4 Metropolitan rankings over time

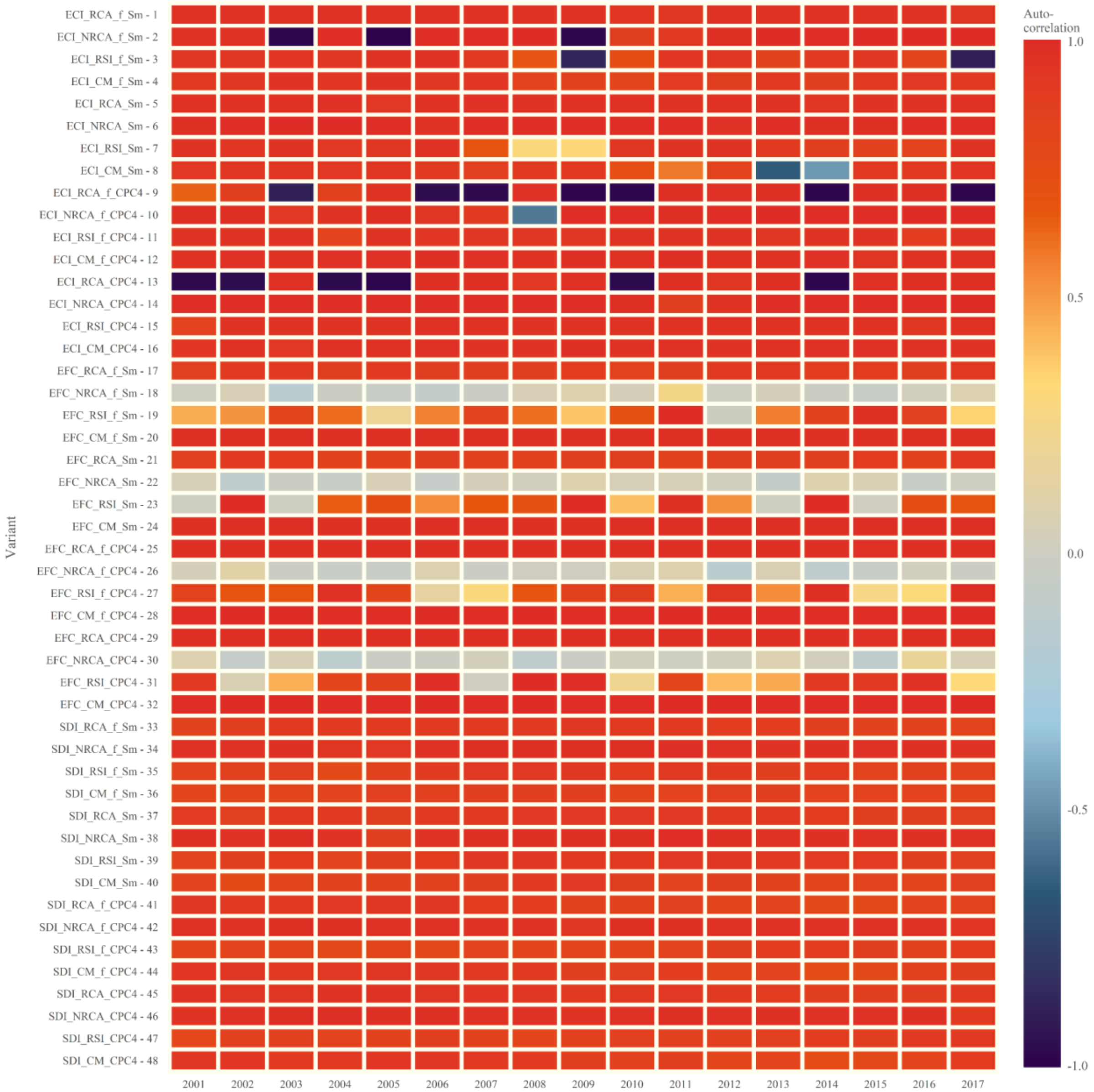
(a) Alternative 1 (ECI, Schmoch, fractional, RCA) (b) Alternative 9 (ECI, CPC4, fractional, RCA)



Note: Both charts depict the metropolitan region codes on the vertical axis and the years on the horizontal axis (2000-2017). All cities are ranked and colored according to their complexity values in the base year.

Rather than reporting bump charts for every single complexity measure, Figure 5 summarizes the information for all alternatives by presenting the correlation coefficients of the complexity scores of 197 metropolitan areas for each of the 48 versions of complexity measures over time. Each of the 48 rows represents one of the 48 complexity measures (Figure 1) and each of the 17 columns represent pairs of years starting with 2000 and 2001 and finishing with 2016 and 2017.

Figure 5 Temporal stability of metropolitan knowledge complexity indices



Note: Numbered variants refer to the alternatives in the knowledge complexity indices depicted in Figure 1. Cells are shaded according to the pearson correlation coefficient of two consecutive years for each alternative and year. For example, shaded cells in column and row one (2001, var.1) refer to the pearson correlation coefficient of results based on alternative 1 in year 2000 and 2001.

Red (high, positive correlation coefficients) shadings signal identical or highly similar complexity scores in two consecutive years whereas blue (high, negative correlation coefficients) shadings correspond to a reversal of rankings in two consecutive years. As expected from Figure 4a, alternative 1 is characterized by high annual correlation coefficients represented by the red shading of all cells. Based on the evolution of metropolitan complexity rankings in Figure 4b, we would expect a number of low or negative correlation coefficients for alternative 9. This is confirmed by Figure 5, with blue shaded cells in columns 3 (negative correlation coefficient between complexity scores of 2002 and 2003), 6, 7, 9, 10, 14, and 17. Based on our plausibility criteria, measures that exhibit little stability in or reversibility of rankings should not be used for policy purposes.

While Figure 5 reveals a rather mixed performance of complexity measures with respect to temporal (in)stability, a few general conclusions can be drawn. First, all versions of the SDI are stable over time. Second, the Economic Fitness Complexity index (EFC) (rows 17-32) is stable for versions with RCA and CM as specialization measures but lacks temporal stability when calculated with NRCA or RSI. This appears to be a result of the non-linear algorithm of the EFC (see second section) that does not work properly when the NRCA or RSI metrics of specializations are used. Third, the pattern emerging from the Economic Complexity Index (ECI) is more complex with excellent temporal stability for some of the alternatives (e.g. ECI, Schmoch, fractional, RCA) and instability for others (e.g. ECI, CPC4, fractional, RCA) [18]. Because the SDI is based on technological complexity (rather than spatial ubiquity) only, the choices of technology classification, fractional counting, or specialization to "spatialize" the index do not seem to have an impact on the temporal stability of the index.

[18] Some of the results make intuitive sense while others are more difficult to explain. For instance, the instability of alternative 8 is likely due to the fact that the CM metric distributes the same specializations for a sizeable number of regions as it accounts for the absolute number of patents in addition to the relative specialization. Hence, in many cases large metropolitan regions receive a specialization in all 35 fields which in turn leads to them having the same complexity score (in the case of the ECI). This effect appears less pronounced when the CM is combined with Schmoch and fractional counting (instability of alternative 8, but not 4).

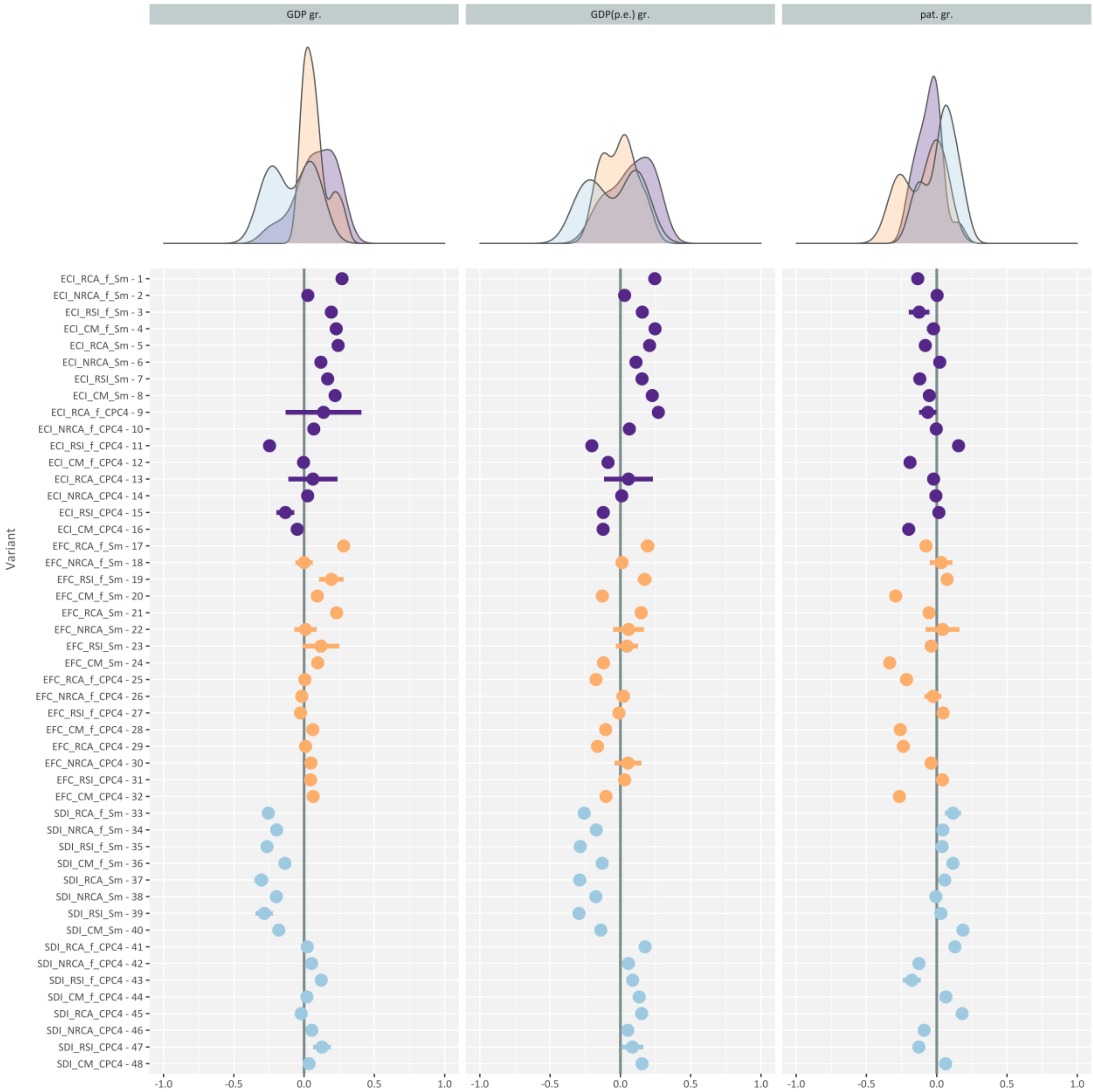
III Complexity and regional growth

One of the reasons for the interest in knowledge complexity is the assumed positive relationship with economic and technological growth. Differences in regional economic development are not only the result of quantitative differences in R&D expenditure or the number of patents but also the quality of innovative output, i.e. the knowledge complexity embodied in a region (e.g. Antonelli *et al.*, 2017, 2020; Mewes and Broekel, 2020; Pintar and Scherngell, 2021; Rigby *et al.*, 2022). We examine the bivariate relationship between the 48 alternative complexity measures and three indicators of growth (GDP growth, (labor) productivity or GDP/employee (emp) growth and growth in the number of patents) by correlating the complexity values with 15-year growth rates in GDP, GDP/emp and the growth in the number of patents[19].

Figure 6 depicts graphically the mean and standard deviations of the correlation coefficients between the 48 alternative complexity score and 15-year growth rates (see footnote 19) and reveals the following pattern: First, the ECI with Schmoch tends to correlate positively with GDP growth and GDP/emp growth but has little impact on the growth of patents. The correlation coefficients of the SDI with Schmoch are negative for GDP and GDP/emp growth but indicate no relationship with patent growth. There is no clear pattern emerging for the different alternatives of the EFC and there is a slight positive relationship for the SDI with CPC-4 and GDP and GDP/emp growth. While we do not suggest that complexity measures should be chosen because of their empirical (bivariate) link with GDP growth, there is an argument for the ECI with Schmoch if the relationship between complexity and GDP growth is at the center of a particular research project. Needless to say that full growth models would need to be estimated to control for potential intervening or confounding variables.

[19] We calculate 5-year moving averages for GDP, GDP/employee and the number of patents in order to smooth out annual fluctuations. GDP2017 is then the five-year average of the GDP of the years 2013-2017, etc. We then calculate 15-year growth rates (GDP2000-GDP2015; GDP2001-GDP2016; GDP2002-GDP2017, etc.) and correlate those with the 48 alternative complexity scores of the base year (e.g. complexity score in 2000 with GDP growth 2000-2015; complexity score 2001 with GDP growth 2001-2016, etc.). This yields three correlation coefficients of which we use the mean and the standard deviation. Both are depicted in Figure 6.

Figure 6 Bivariate correlation coefficients between knowledge complexity and regional growth



Note: Points reflect the contemporaneous correlation of alternatives of the complexity index with indicators of regional growth. Horizontal bars represent one standard deviation (over time) distance from the correlation coefficient (mean) on both sides. Many correlation coefficients are so stable over time that the standard deviation is not visible as bars do not extend beyond the point. Color is used to distinguish between measures of knowledge complexity indices. “GDP gr.”, “GDP(p.e.) gr.” And “pat. gr.” stand for 15-year growth of logged regional GDP, logged GDP per employee (labor productivity) and patent growth, respectively.

CONCLUSION

This paper offered a first systematic comparison of different complexity measures applied to a consistent set of patent data for 197 European metropolitan regions for the period 1996-2017. Differences between territorial and technological complexity indices can thus be attributed to different choices of complexity measures and empirical operationalizations of them rather than differences in data sources, time frame or sample variation. Furthermore, the paper compared a number of alternatives already employed in the literature and added a number of new alternatives that are interesting from a theoretical and conceptual point of view (especially with respect to calculating regional specializations in particular knowledge classes/fields). And finally, the paper illustrated that the choice of various measures to calculate empirical regional and technology complexity values are not trivial but lead to widely differing results that have an influence on the policy conclusions that follow from them. If we go back to Figure 1 and apply our evaluation criteria to try and eliminate variations based on their temporal stability criteria and then choose among the remaining alternatives those that appear most correlated with indicators of regional development, we would end up with the results presented in Figure 7 (see below).

Rather than suggesting that policy makers and researchers should mechanistically apply the results of this analysis to inform smart specialization policies in practice, our conclusions and recommendations are much more modest and invite to caution more than offer prescriptions. Because there are no good theoretical or conceptual reasons to adopt one complexity measure over another, we do need more theoretical and conceptual work that would offer better guidance for choosing "the" suitable measure before it is widely applied to guide funding decisions. We would also recommend to choose a portfolio of complexity measures (the programs to do so are widely available) to get a sense of the sensitivity of policy recommendations to the choice of complexity measures in particular contexts. And finally, it makes sense to form prior expectations and hypotheses based on a researcher's knowledge of a particular region or technology field to be able to evaluate the results. Hence, while the implementation of knowledge complexity measures may introduce a general mechanistic (and efficient) implementation guideline for smart specialization policies it will not be able to replace experts and their in-depth knowledge of the current research strengths and portfolios, industrial and product specializations of companies or the strength and weaknesses of research institutions in particular local contexts.

Figure 7 Eliminated and selected complexity measures

Complexity measure	Technology	Counting	Spec.	Var.	Comparable applications
Economic Complexity Index (ECI)	Schmoch	fractional	RCA	1	(Balland et al., 2019), (Whittle, 2019), (Pintar and Scherngell, 2021)
		~~fractional~~	~~NRCA~~	~~2~~	
			~~RSI~~	~~3~~	
			CM	4	
		double	RCA	5	
			NRCA	6	
			~~RSI~~	~~7~~	
			~~CM~~	~~8~~	
	CPC4	fractional	~~RCA~~	~~9~~	~~(Balland and Rigby, 2017), (Ivanova et al., 2017)~~, (Rigby et al., 2019)
			~~NRCA~~	~~10~~	
			RSI	11	
			CM	12	
		double	~~RCA~~	~~13~~	~~(Antonelli et al., 2017), (Antonelli et al., 2020)~~
			NRCA	14	
			RSI	15	
			CM	16	
Economic Fitness Complexity Index (EFC)	Schmoch	fractional	RCA	17	
		~~fractional~~	~~NRCA~~	~~18~~	
			~~RSI~~	~~19~~	
			CM	20	
		double	RCA	21	
			~~NRCA~~	~~22~~	
			~~RSI~~	~~23~~	
			CM	24	
	CPC4	fractional	RCA	25	(Sbardella et al., 2018)*, (Napolitano et al., 2020)*, (Sbardella et al., 2021)**
			~~NRCA~~	~~26~~	
			~~RSI~~	~~27~~	
			CM	28	
		double	RCA	29	
			~~NRCA~~	~~30~~	
			~~RSI~~	~~31~~	
			CM	32	
Structural Diversity Index (SDI)+	Schmoch	fractional	RCA	33	
			NRCA	34	
			RSI	35	
			CM	36	
		double	RCA	37	
			NRCA	38	
			RSI	39	
			CM	40	
	CPC4	fractional	RCA	41	(Broekel, 2019), (Juhász et al., 2020), (Mewes and Broekel, 2020)
			NRCA	42	
			RSI	43	
			CM	44	
		double	RCA	45	
			NRCA	46	
			RSI	47	
			CM	48	

Sources: ECI: (Hidalgo and Hausmann, 2009), (Caldarelli et al., 2012); EFC: (Tacchella et al., 2012); SDI: (Broekel, 2019), (Emmert-Streib and Dehmer, 2012); Schmoch: (Schmoch, 2008); RCA: (Balassa, 1965); normalized revealed comparative advantage (NRCA): (Yu et al., 2009); relative specialisation index (RSI): (Menzel and Maicher, 2017); composite matrix (CM): (Fritz and Manduca, 2021).

Note: +In contrast to ECI and EFC, SDI is defined only on the technological level. Since we compare complexity measures in a policy context and on a regional level, we attribute SDI values to regions via a weighted average of the regions technological portfolio.*Papers focus on a subset of "green" technologies on different technological levels, are not directly comparable to CPC4. **This study uses CPC classes but not exclusively CPC4.

Legend:

Eliminated based on temporal stability criteria

Chosen if link to economic or (labor) productivity growth is of interest

Chosen if link to (labor) productivity growth (only) is of interest

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