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A composite indicator analysis for optimizing entrepreneurial ecosystems

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ABSTRACT

We employ the 'benefit of the doubt' approach rooted in non-parametric techniques to evaluate the entrepreneurial ecosystem of 71 countries for the period 2016. By scrutinizing the relative efficiency of countries' entrepreneurial ecosystems, the proposed analysis of composite indicators allows the computation of endogenous (country-specific) weights that can be used for developing more informed policy making. The results show that countries prioritize different aspects of their national system of entrepreneurship which confirms that, contrary to homogeneous prescription, tailor-made policy is necessary if the objective is to optimize the resources deployed to enhance the countries' entrepreneurial ecosystem. The findings of the empirical application reveal significant improvements in the quality of the entrepreneurial ecosystem can be realized by targeting the policy priorities of the local entrepreneurship system identified by the 'benefit of the doubt' weights. By analyzing the variation in economic and entrepreneurship outcomes over the seven-year period centered on the study year (period 2013–2019), we found a significant positive correlation between quality improvements in the entrepreneurial ecosystem and venture capital investments.

JEL codes: C14, C43, C61, L26

1. Introduction

As a national phenomenon, entrepreneurship is much more than the mere rate of new businesses in the economy. By acknowledging that country-level entrepreneurship is a multidimensional construct shaped by multiple interactions between economic agents and the institutional setting backing entrepreneurial action, the concept of entrepreneurial ecosystem has become a 'trendy' topic within academic and policy communities (Acs et al., 2014; Autio et al., 2015). Countries cover a wide range of institutional settings, thus it is plausible to argue that the entrepreneurial ecosystem is governed by complex social and institutional interactions. This view is consistent with recent work emphasizing that the ecosystem's complexity—which results from its multidimensionality and materializes in different country-specific configurations—leads to different national outcomes (e.g., Brown and Mason, 2017; Spigel, 2017; Stam and Van de Ven, 2021). At this point, an important question is how entrepreneurial ecosystem analyses can be reconciled with the mainstream view that these two properties—i.e., complexity and geographic heterogeneity—condition both the configuration and the economic impact of this ecosystem.

By accounting for the inherent complexity and geographic heterogeneity of entrepreneurial ecosystems, an analysis based on a composite indicator (CI, hereafter) may well be more appropriate to obtain a more realistic picture of this ecosystem and its role on the economy. Composite indicators have gained increased popularity among scholars and policy makers mostly because they compile into a single metric a complex phenomenon that cannot be fully captured with one variable, thus facilitating its communication and understanding (Booysen, 2002; Cherchye et al., 2007a). Also, CIs represent an alternative to statistical models with potentially limited practical application that neglect the multidimensionality of the phenomenon that the CI attempts to quantify and evaluate (Friedman and Schwartz, 1991). Thus, CIs have become a valuable tool for policy makers interested in identifying benchmarks and trends as well as setting policy priorities (Organization for Economic Cooperation and Development (OECD) 2008). Studies based on CIs have been used in different fields including, among others, economics (e.g., internal market index, global competitiveness index or county competitiveness), human development (e.g., human development index), and quality of life (e.g., better life index) (Cherchye et al., 2007a; Despotis, 2005; Lafuente et al., 2020; Mizobuchi, 2014).

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Nevertheless, CIs are not exempt from criticism. First, CIs are criticized by the subjectivity of their construction. Conceptual criticism mostly highlights the lack of scientific consensus about what theoretical model should provide a detailed description of the variables used to explain the studied phenomenon (Cherchye et al., 2008). Subjective choices condition the way CIs answer relevant questions related to the phenomenon that CIs attempt to summarize (Booysen, 2002). The second source of criticism is linked to the absence of clear guidance on the weighting system that should be applied to the CI sub-indicators. Weights are decisive elements of CIs as they determine the trade-offs between the selected variables. Weights condition CI results which may lead to inaccurate conclusions if subjective criteria are used to set weights (Grupp and Schubert, 2010; Mizobuchi, 2014).

In the specific context of this study, the increased demand of CIs observed among policy observers does not seem to have empirical correspondence in the entrepreneurship literature. In this sense, the analysis of CIs designed to evaluate the quality of entrepreneurial ecosystems is the focus of this study. Despite the relevance of the entrepreneurship to the economy, scholars acknowledge the difficulties in operationalizing this construct at country level (e.g., Acs et al., 2016; Aghion, 2017). Existing research mostly uses index metrics (i.e., output / input) based on either firm-level (e.g., new firms divided by the stock of firms) or individual-level data (e.g., the total entrepreneurial activity created by the Global Entrepreneurship Monitor, GEM[1]) to inform policy makers and assess the role of entrepreneurship on the economy. The observed mismatch between the analyzed concept (entrepreneurial ecosystem) and the measurement approach (firm- and individual-level data) may well explain the inconclusive results reported in prior work dealing with country-level entrepreneurship and its repercussions at national and sub-national levels (Acs et al., 2018; Naudé, 2011).

Recently, Acs et al. (2014) proposed a CI—namely, the Global Entrepreneurship Index (GEI)—to measure the quality of countries' entrepreneurial ecosystem by capturing the systemic interactions between entrepreneurial action and country-specific institutional characteristics. The focus of the GEI is not on R&D processes or the process of entrepreneurship but on the structure of the national systems that affect technical change. The analysis of entrepreneurial ecosystems based on the GEI provides a rich framework to understand how entrepreneurship and the interactions between individuals and the context nurture economic performance (Lafuente et al., 2020).

The GEI quantifies the overall level of the entrepreneurial ecosystem for each country (i) as the weighted sum of 14 pillars (j) ($\sum w_j \times h_{ij} = GEI_i \forall w_j = 1/14$). This weighting system reflects a value judgment on what is considered a good entrepreneurial ecosystem. This approach, based on homogeneous (across countries) and fixed (across variables) weights, ignores countries' heterogeneity which may obscure policy recommendations. By construction, additional resources to improve GEI pillars (raw data) would quantitatively yield the same new GEI score, as which pillars are improved have no effect on the final score. Partial solutions have been proposed to address this issue (e.g., the penalty for bottleneck in the case of the GEI[2]). Without objective guidance policy makers will likely follow discretionary criteria to allocate the extra resources, and the quantity improvement of the GEI will be interpreted as good news. On contrary, if policy makers are given more objective, non-arbitrary information about the importance of GEI pillars, resource allocation should follow a more economically meaningful process. Quantity improvements are ensured if additional resources are deployed and, for an equal quantitative improvement in the GEI, enhancements in the GEI will be qualitatively superior if policy makers are better informed and have a clear set of policy priorities.

The GEI has attractive properties that certify its accuracy to measure countries' entrepreneurial ecosystem. But, in light of the importance of weights both for computing CIs and for identifying key indicators and policy priorities two relevant research questions arise: how would the quality analysis of entrepreneurial ecosystems based on CIs differ when endogenous weights capturing countries' heterogeneity are included in the model? Moreover, and given that the importance of GEI pillars is not homogenous across economies, does an analysis of entrepreneurial ecosystems based on CIs help to unveil economically meaningful policies which can impact relevant country-level outcomes?

To answer these questions empirically, the main objective of this paper is to evaluate the quality of the entrepreneurial ecosystem of 71 countries for 2016. By using a non-parametric CI approach, the proposed analysis can be used to promote quality-led improvements in the entrepreneurial ecosystem.

The entrepreneurial ecosystem can significantly impact the economy (Lafuente et al., 2020); however, entrepreneurial ecosystems are not checklists that can be easily altered in the short term. Thus, we employ event-study method to assess how quantity and quality changes in the entrepreneurial ecosystem impact countries' performance. Specifically, we examine data for the seven years centered on the study period (2016) to test whether CI changes between 2013 and 2019 correlate with changes in economic (GDP per capita) and entrepreneurial (venture capital investments) outcomes, and whether the reported performance changes are more pronounced in countries whose entrepreneurial ecosystem improved following the strategies identified by our CI analysis.

For the CI application we employ the 'Benefit of the Doubt' (BOD) weighting method, originally developed by Melyn and Moesen (1991) and used by, among others, Cherchye et al. (2007b; 2008), Mahlberg and Obersteiner (2001), OECD (2008) and Sahoo et al. (2017). Rooted in non-parametric techniques (i.e., Data Envelopment Analysis, DEA), the BOD weighting is an optimization method that employs linear programming to compute country-specific, non-arbitrary weights for a set of outputs—in our case, the 14 GEI pillars—such that the resulting configuration optimizes countries' CI score. Thus, the proposed BOD model (BOD-GEI) identifies GEI pillars that a focal country should prioritize if a quality improvement in the entrepreneurial ecosystem is the desired goal.

Although the BOD weighting model is among the techniques recommended by the OECD (2008) for computing CIs; it is worth questioning why countries should be given the benefit of the doubt when it comes to evaluate their entrepreneurial ecosystem. As any CI, the purpose of the GEI is to rank countries, identify benchmarks and inform policy makers on the most relevant constituents of the entrepreneurial ecosystem. The chosen weighting scheme—either normative (equal weights and expert-based) or data-driven (BOD)—is decisive to achieve these purposes; but obviously a flawless weighting method does not exist (Cherchye et al., 2007a; Decancq and Lugo, 2013).

For the specific purpose of this study, the BOD method is more suitable for our analysis for, at least, two interrelated reasons. First, from a methodological point of view, normative approaches impose partial rigidity to CIs either by assuming that all variables are equally important across units and across variables (equal weights method), or by fixing weights across units while allowing weight heterogeneity across variables (expert-based methods) (Cherchye et al., 2007b). Second, from a policy perspective, every country has its own social and economic priorities and what can be considered a desirable policy in one country may not be so in another context. The flexibility of the BOD model supports this argument. Mimicking policies adopted by advanced countries in

[1] Based on the GEM's methodology, the total entrepreneurial activity (TEA) measures the proportion of nascent entrepreneurs—who are actively involved in the business creation process—and new firms—up to 3.5 years old—relative to the total active population (individuals aged 18-64 years) (Acs et al., 2014).

[2] The penalty for bottleneck (PFB) method works under the questionable assumption that improvements in the weakest pillar produce the greatest improvement in the GEI index (Section 2). Thus, and following the tradition in CI analyses (e.g., Cherchye et al., 2007a; 2008; Sahoo et al., 2017), our CI approach is based on the analysis of raw data to obtain a cleaner evaluation of CIs (details on this issue are presented in Section 3).

developing economies without proper adaptation to the socioeconomic context would not help to improve the quality of the entrepreneurial ecosystem in these countries. By computing endogenous, non-arbitrary weights, the BOD model recognizes territorial heterogeneity and allows countries to identify the most relevant aspects of their entrepreneurial ecosystem based on their specific institutional and market conditions.

CI analyses should match both the geographic diversity and complexity of the analyzed phenomenon. In this sense, what is the position of our study within the entrepreneurship literature? Although there is no perfect recipe to build a universally accepted and generalizable CI, the detailed nature of the study data (GEI) and the proposed analysis should provide enough feedback into the generation of economically meaningful CIs.[3] Therefore, the importance of this study stretches beyond a purely computational exercise and has potentially relevant implications for the entrepreneurial ecosystem literature. Our CI approach contributes to unveil policy priorities which, in turn, have the potential to show policy makers how to orchestrate resources in order to fully realize the benefits of a qualitatively superior entrepreneurial ecosystem. Also, by correlating directed changes in CI values with variations in economic and entrepreneurial outcomes, the key findings of our study help to grasp how qualitative variations in entrepreneurial ecosystems impact national outcomes.

The next section presents the background theory. Section 3 describes the data and the 'Benefit of the Doubt' approach for CI analyses. Section 4 presents the empirical results, while the discussion and concluding remarks are offered in Section 5.

2. The entrepreneurial ecosystem

The trajectory of change observed in most economies during the last decades (e.g., institutional reforms that promote innovations and entrepreneurship, or the rapid digitalization of the economy) has fueled the debate on the relevance and the economic possibilities of country-level entrepreneurship (Acs et al., 2014). In this discussion, entrepreneurship has been invoked as a conduit mechanism of economic growth and innovation (Aghion, 2017; Schumpeter, 1934). However, the outcomes of entrepreneurship are conditional on the environment within which they take place (Autio et al., 2015). Thus, it is the institutional setting and not the stock of entrepreneurs that dictates the ultimate effect of entrepreneurship on countries' economic results (Baumol, 1990; Lafuente et al., 2020).

Because institutional environments, including the setting governing entrepreneurship, are characterized by the presence of multiple overlapping stakeholders, scholars highlight the need to account for the interactions between institutions and economic agents that take place within and between territories (Acs et al., 2014; Lafuente et al., 2020; Radosevic and Yoruk, 2013). In this sense, the entrepreneurial ecosystem approach has gained increased popularity.

The entrepreneurial ecosystem has been conceived as a dynamic, institutionally embedded umbrella that encourages the interaction between mutually connected stakeholders which, in turn, supports resource mobilization, entrepreneurial action and the outcomes of new and incumbent firms (Acs et al., 2014; Autio et al., 2015). Rooted in ecological metaphors originally proposed by Moore (1993) and popularized by Isenberg (2010), the core concepts underlying the entrepreneurial ecosystem are grounded in solid literature frames: the national innovation system (Freeman, 1995; Lundvall, 1992), the cluster-based theory of competitive advantage (Delgado et al., 2010; Porter, 1998), regional innovation systems (Cooke et al., 1997; Fritsch, 2001), and the national innovative capacity (Furman et al., 2002). These literatures show important conceptual and methodological differences, and they have mostly treated entrepreneurship as a factor that is peripheral to their focus of study. The entrepreneurial ecosystem approach offers a way to unify these theories by emphasizing the role of 'place' and providing a renewed lens for better grasping how the connections between different stakeholders contribute to regional transformation through entrepreneurial action.

Entrepreneurial ecosystems are not checklists. Academic work theorizing this ecosystem mostly agrees in defining and identifying its constituents (see, e.g., Acs et al., 2014; Autio et al., 2015; Spigel, 2017); however, the debate on the mechanics underlying the ecosystem is still open. Thus, in order to understand the value of the analysis proposed in this study, it is important to clarify the theoretical connection between the entrepreneurship ecosystem and economic outcomes, as well as the mechanics governing the coordination between the different ecosystem essential components.

The elements of the entrepreneurial ecosystem—i.e., social, economic, and institutional factors—do not work in isolation and their individual assessment would not produce accurate results. The essential aspect of entrepreneurship is not the number of new firms. Instead, the coordinated actions across stakeholders within a geographically bounded space allude to the networked relations that define the ecosystem's configuration, while acknowledging that territorial heterogeneity—e.g., institutions and entrepreneurial activity (Brown and Mason, 2017; Prieger et al., 2016)—explains the emergence of different configurations whose effectiveness can also be case-specific.

The constituents of the entrepreneurial ecosystem cannot be organized in a simple hierarchy (Spigel, 2017). Observable outcomes of this ecosystem are often linked to, among others, startup rates, venture capital activity, university-industry collaborations and, indirectly, to macroeconomic figures (Acs et al., 2018; Lafuente et al., 2020; Radosevic and Yoruk, 2013). Because of the impossibility for drawing all the relationships taking place among ecosystem participants, the full understanding of the mechanics of entrepreneurial ecosystems is a difficult, challenging task. Nevertheless, prior studies offer valuable insights on the factors explaining the functioning of entrepreneurial ecosystems.

First, multi-sided coordination—whether planned or unplanned—is a key aspect for entrepreneurial ecosystems to work (Acs et al., 2018; Autio and Levie, 2017). This mechanism does not imply the adoption of fragmented policies to attract entrepreneurs or investors which, in many cases, show poor results (Minniti, 2008). Instead, we argue that the role of entrepreneurship policy should be one of facilitator rather than regulator, and one that seeks to enhance the ecosystem components rather than supporting isolated actions with limited economic impact. Second, in a related manner, ecosystem-enhancing policies would turn sterile in the absence of social legitimacy (Lafuente et al., 2007; Feldman, 2001). The approval of the community to the adopted policies can stimulate the local entrepreneurial culture, fuel local networks, and attract more investors and entrepreneurs to the territory (Spigel, 2017). Thus, it can be suggested that social legitimacy acts as a sort of glue that binds together policy makers and the stakeholders that participate in the local ecosystem.

Third, the functioning of any entrepreneurial ecosystem is reliant on the ability of entrepreneurs and businesses to exploit local resources, as well as the territories' capacity to create supportive environments for entrepreneurship. Research on both consolidated—e.g., Silicon Valley (Saxenian, 1994) or Singapore (Wong et al., 2007)—and developing ecosystems—e.g., Estonia (Kshetri, 2014) or Waterloo (Spigel (2017)—suggests that distinctive properties of the areas where ecosystems develop might explain their geographic concentration. These factors include, among others: the presence of specific resources (e.g., skilled workers, venture capitalists) (Prieger et al., 2016), physical and digital infrastructures (Autio et al., 2018), and social support to

[3] Note that, as any CI, the GEI is a static measure. Thus, it may well be the case that policies promoting change in the entrepreneurial ecosystem by allocating additional resources have no effect on the GEI if the processes and outcomes of these policies are not evident in the short term, that is, they impact (one or more) GEI pillars in the mid- or long-run. We thank one of the anonymous referees for this valuable observation.

entrepreneurship (Feldman, 2001).

In our view, the geography of entrepreneurial ecosystems—i.e., national-level entrepreneurship policy with localized effects—can be viewed as the observable consequence of the successful interactions between various ecosystem elements: the coordination (whether planned or not) between stakeholders who have incentives to exploit business opportunities (Pitelis, 2012); and the development of a configuration where the efficient allocation (and concentration) of resources is coupled with the development of strong networks supporting entrepreneurship (Spigel, 2017).

The prevailing characteristics of the entrepreneurial ecosystem can be described and improved. However, policy makers often do not have the information means to know how to do this task, and reforms tend to cater to the tastes of policy makers, that is, the quantitative revival of the entrepreneurial spirit (Lafuente et al., 2020). But if what is needed is the implementation of directed policy to induce the fertilization of the ecosystem, then solutions to identify such policies are required.

Complexity and geographic heterogeneity characterize entrepreneurial ecosystems. Complexity implies that to understand the functioning of the ecosystem we need to study the multidimensionality and interconnectivity between stakeholders that typify the ecosystem. Based on the premise that ecosystem constituents are heterogeneous across economies, we argue that entrepreneurship policy should be case-specific rather than imitative and account for the properties of the country's institutional setting. Following this line of thinking, the match between complexity and geographic heterogeneity is an essential prerequisite for an effective analysis of entrepreneurial ecosystems.

This is the core of our study. By proposing a model that determines what ecosystem constituents should be prioritized if an enhanced ecosystem is the desired goal, while acknowledging the heterogeneity of countries' entrepreneurial ecosystem; we can estimate the relative importance of the ecosystem's building blocks, as well as the expected improvements in the quality of the ecosystem if a tailor-made and more informed entrepreneurship policy is implemented.

3. Analysis of composite indicators (CIs) using the 'Benefit of the doubt' (BOD) approach

An important task of policy makers is to rank the available alternatives based on some evaluation criteria. Summarizing a number of variables into a single CI entails making judgments about the importance of each variable, and the difficulty of this task increases with the number of alternatives. Policy makers should also learn that their decisions affect both the targeted goals and other elements of the system. Thus, policy actions cannot be evaluated in isolation but rather in terms of the performance of all metrics forming the analyzed system (De Laurentis and Callaway, 2004).

A central point of this paper is to provide a CI analysis that is suitable for tailor-made policy recommendations. Thus, in this study we aggregate the 14 pillars (equations (A3)-(A5) in Appendix 1) of the GEI into a CI in order to assess the quality of the entrepreneurial ecosystem in 71 countries.

Because the weight assigned to variables is critical to generate economically meaningful policies, we employ the 'Benefit of the Doubt' (BOD) weighting—originally proposed by Melyn and Moesen (1991) and further developed by, among others, Cherchye et al. (2007a; 2008)—to compute endogenous (country-specific), non-arbitrary weights for the 14 GEI pillars that permit us to identify priorities which may become targets for policies aimed at enhancing the entrepreneurial ecosystem.

The BOD approach is rooted in non-parametric techniques, namely Data Envelopment Analysis (DEA) (e.g., Cooper et al., 2011; Grifell-Tatjé and Lovell, 2015; Ray, 2004). DEA is a benchmarking tool that employs linear programming to evaluate the relative efficiency of a set of units by estimating their distance to the production frontier. Contrary to parametric methods (e.g., stochastic frontier), DEA allows to model a technology with multiple outputs without imposing any assumption on the function distribution, which is especially relevant for our study (Grifell-Tatjé and Lovell, 2015). A flexible function is ideal in cases where information about the true technology is limited and the core of the analysis is the identification of the weights assigned to each output. The primary technological assumption of DEA is that countries (i) use a set of $\mathbf{x} = (x_1, \dots x_M) \in R_+^M$ inputs to produce a set of $\mathbf{y} = (y_1, \dots, y_J) \in R_+^J$ outputs, and that these sets form the technology (T):$T = \{(\mathbf{x}, \mathbf{y}) : \mathbf{x} \text{ can produce} \mathbf{y}\}$

Specifically, the BOD weighting is a special case of the input-oriented DEA model with a single constant input (Cherchye et al., 2007b; Liu et al., 2011; Lovell and Pastor, 1999). The BOD approach exploits one of main properties of DEA models: the information on the efficient weighting of outputs for performance benchmarking can be generated from the observed data. Underlying this intuition is the idea that, for any observed country, a relatively good performing indicator points to the relevance of this policy dimension for the focal country. Put it differently, that a country gives less importance to certain dimensions is evidence that it is a weak performer relative to the rest of countries in the dataset.

Therefore, the optimal weighting configuration can be empirically generated for each country by identifying the relative strengths and weaknesses of the analyzed outputs. Without information about the exact weights of the 14 GEI pillars ($\mathbf{y}$), the BOD model assigns to each country the best possible weight configuration, relative to other countries in the sample.

The following linear program computes, for each country (i), the BOD model used to generate the endogenous set of optimal weights for the 14 GEI pillars (Cherchye et al., 2007b; 2008):

$$\begin{gathered} \mathrm{BOD}-\mathrm{GEI}_i = \max \sum_{j=1}^{14} w_{ij} y_{ij} \\ \text{subject to} \sum_{j=1}^{14} w_{ij} y_{ij} \leq 1 i = 1, \dots, N \\ w_{ij} \geq 0 j = 1, \dots, 14 \\ L_j \leq \frac{w_{ij} y_{ij}}{\sum_{j=1}^{14} w_{ij} y_{ij}} \leq U_j L_j = (1/14) \times 0.25 \wedge U_j = (1/14) \times 1.25 \end{gathered} \tag{1}$$

Eq. (1) computes for each country a vector of endogenous weights for the 14 GEI pillars ($w_j = w_1, \dots, w_{14}$) that maximizes the BOD-GEI. The BOD-GEI values are bounded($BOD - GEI_i \leq 1$), where BOD-GEI = 1 for efficient countries (on the production frontier) and for countries below the frontier BOD-GEI < 1 (1–BOD-GEI is the estimated relative inefficiency). Weights are constrained to be non-negative($w_{ij} \geq 0$), which makes the BOD-GEI a non-decreasing function of the output set.

The non-negativity constraint on the weights allows for extreme scenarios that render the results inaccurate by artificially positioning many countries on the frontier. Additional weight restrictions are needed in order to account for the importance of all GEI pillars. The definition of weights for individual variables is a complex task. There is no perfect weighting method, and prior work has employed a normative (equal weights or expert-based) or a data-driven (BOD) approach (e.g., Araya-Solano, 2019; Cherchye et al., 2007a, 2008; Decancq and Lugo, 2013; Lafuente et al., 2020).

A normative model based on equal weights imposes unrealistic rigidity by assuming that, for all units, all CI variables are equally important. Expert-based weighting partially relaxes this assumption by allowing weight heterogeneity across variables; however, this approach does not account for units' heterogeneity (i.e., weights are fixed across countries) (Lafuente et al., 2020). Although the value of this information rich method, expert-based weighting relies entirely on experts' judgment, which can compromise CI results if experts' opinions are inconsistent, volatile or strongly aligned with policy makers' agenda (Decancq and Lugo, 2013). Data-driven models (e.g., the BOD) maximize CI scores without prior information on the variables' weights. The BOD model allows for weight heterogeneity across variables and across units, which constitutes its more attractive property. But, by ignoring experts' view the BOD method can produce potentially unreliable or hard-to-interpret results.

This study employs the BOD method. By computing endogenous, non-arbitrary weights to the GEI pillars the BOD approach assumes that countries have their own policy priorities, in terms of the entrepreneurial ecosystem, and, consequently, optimal policy should be country specific.

Because the core of our study is the generation of valuable information for tailor-made policy making, we add to the BOD-GEI model (Eq. (1)) a 'pie share' restriction (Cherchye et al., 2007b): $L_j \leq \frac{w_{ij}y_{ij}}{\sum_{j=1}^{14} w_{ij}y_{ij}} \leq U_j$. This proportional restriction is especially attractive because pie shares $(w_{ij}y_{ij})$ do not depend on measurement units and they directly reveal the contribution of each pie share to the BOD-GEI, while allowing for weight heterogeneity within and between countries. Similar to prior work (Cherchye et al., 2008, 2011), L_j and U_j are the lower $((1/14) \times 0.25)$ and upper $((1/14) \times 1.25)$ bound set for each 'pie share'. That is, countries can freely choose their output weights(w_{ij}) conditional on the two set constraints: non-negativity and bounded 'pie shares'.

Therefore, the 'pie share' constraint in Eq. (1) allows for a more realistic modeling of the countries' entrepreneurial ecosystem function and contributes to our primary objective: to identify country-specific policy priorities that permit us to know what aspects of the GEI index should be targeted in order to produce significant quality improvements in the entrepreneurial ecosystem.

For the empirical analysis, the information on the GEI pillars was obtained from the Global Entrepreneurship Development Institute (www.thegedi.org). Recent work acknowledges the value of the GEI as a robust variable to measure the quality of the countries' entrepreneurial ecosystem (Acs et al., 2018; Lafuente et al., 2020). Also, a simple correlation analysis reveals the positive association between the GEI and GDP per capita (Fig. 1), and this further validates the informational power of GEI as a measure of countries' entrepreneurial ecosystem (Acs et al., 2018; Lafuente et al., 2020).

A detailed description of the GEI methodology is presented in Appendix 1. The final sample includes 71 countries: 12 African economies; 19 American countries (North America, Latin America and the Caribbean); 9 Asian countries, and 31 European economies. Data on the GEI scores for 2012 and 2016 are presented in Table 1, while Table 2 shows the descriptive statistics for the 14 GEI pillars (Acs et al. (2017): y1=

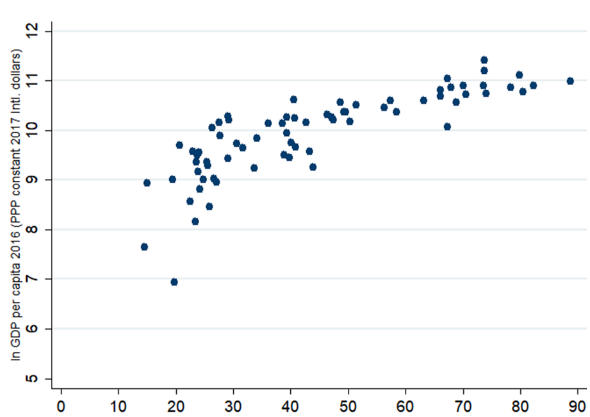

Fig. 1. The relationship between the GEI index and GDP per capita. Note: Bivariate correlation = 0.8129 (p-value < 0.0000). Number of observations: 71 countries. Source: The Global Entrepreneurship Development Institute (GEI scores) and the World Bank (log value of the GDP per capita, expressed at 2017 prices in PPP, constant international dollars).

Table 1
The Global Entrepreneurship Index in 2012 and 2016 (normalized values): Country ranking.

N	Country	GEI 2016 (GEI 2012)	N	Country	GEI 2016 (GEI 2012)
1	United States	88.51 (85.37)	38	Hungary	39.47 (43.53)
2	Denmark	85.33 (83.05)	39	South Africa	38.61 (39.54)
3	Switzerland	84.38 (81.34)	40	Romania	38.59 (37.56)
4	Canada	83.54 (80.31)	41	Botswana	38.14 (37.44)
5	Ireland	82.62 (72.55)	42	Malaysia	37.47 (42.18)
6	United Kingdom	80.48 (72.78)	43	Costa Rica	34.09 (34.04)
7	Sweden	77.89 (78.38)	44	Namibia	33.65 (34.12)
8	Netherlands	76.26 (75.16)	45	Panama	32.20 (30.72)
9	Finland	74.35 (77.48)	46	Peru	31.21 (32.54)
10	Singapore	73.72 (73.19)	47	North Macedonia	31.09 (32.30)
11	Germany	71.69 (67.47)	48	Thailand	30.17 (31.05)
12	Austria	71.61 (72.06)	49	Mexico	28.95 (31.94)
13	France	70.93 (71.11)	50	Russia	28.50 (26.42)
14	Norway	67.39 (69.99)	51	Argentina	28.34 (30.63)
15	Belgium	66.06 (68.81)	52	Philippines	27.07 (25.39)
16	Israel	65.44 (63.37)	53	Iran	26.85 (21.80)
17	Chile	65.32 (66.78)	54	Ghana	25.84 (23.88)
18	Estonia	63.18 (60.02)	55	Jamaica	25.39 (23.82)
19	Japan	63.15 (57.50)	56	Algeria	25.14 (22.08)
20	Korea	61.65 (55.85)	57	Trinidad & Tobago	25.26 (28.28)
21	Slovenia	58.22 (58.67)	58	Egypt	25.18 (22.67)
22	Poland	53.42 (48.37)	59	Bolivia	24.81 (17.34)
23	Czech Republic	51.38 (53.54)	60	Bosnia & Herzegovina	23.72 (22.41)
24	Portugal	51.16 (48.56)	61	Vietnam	23.58 (24.61)
25	China	50.07 (39.50)	62	Zambia	23.41 (24.91)
26	Lithuania	49.59 (46.00)	63	Brazil	23.27 (24.68)
27	Spain	49.40 (50.67)	64	Guatemala	22.61 (17.36)
28	Slovakia	48.55 (44.20)	65	Nigeria	22.44 (24.33)
29	Turkey	47.51 (44.18)	66	Ecuador	22.01 (22.16)
30	Italy	45.84 (42.41)	67	Suriname	20.68 (21.48)
31	Latvia	43.84 (45.64)	68	El Salvador	18.33 (24.84)
32	Tunisia	43.91 (36.72)	69	Angola	14.88 (14.55)
33	Greece	43.75 (39.41)	70	Uganda	14.50 (14.35)
34	Colombia	42.06 (43.45)	71	Malawi	13.67 (21.52)
35	Barbados	40.78 (38.40)			
36	Croatia	39.89 (37.05)			
37	Uruguay	39.67 (38.63)			

Source: The Global Entrepreneurship Development Institute (www.thegedi.org). Countries are ranked based on the GEI 2016 values. GEI values for 2012 are presented in parentheses.

Table 2
GEI index: Average pillar values.

GEI pillars	Africa	America	Asia	Europe	Total
Opportunity Perception	41.10	48.90	28.17	51.32	46.01
Startup Skills	12.98	48.22	30.26	56.51	43.61
Risk Acceptance	25.30	36.68	42.88	53.73	42.99
Networking	33.43	41.66	39.70	45.29	41.60
Cultural Support	34.85	41.71	33.06	54.72	45.13
Opportunity Startup	27.55	34.00	45.18	59.06	45.27
Technology Absorption	20.30	24.54	38.29	64.11	42.84
Human Capital	25.86	39.19	59.54	51.21	44.76
Competition	32.22	41.08	37.34	52.96	44.30
Product Innovation	27.37	37.40	53.42	53.20	44.63
Process Innovation	27.49	22.21	55.94	61.29	44.44
High Growth	28.11	35.88	45.34	50.40	42.11
Internationalization	24.40	33.01	36.97	65.87	46.41
Risk Capital	22.91	29.35	47.42	58.02	43.07
Number of countries	12	19	9	31	71

Source: The Global Entrepreneurship Development Institute (www.thegedi.org).

Opportunity perception, y2= Startup skills, y3= Risk acceptance, y4= Networking, y5= Cultural support, y6= Opportunity startup, y7= Technology absorption, y8= Human capital, y9= Competition, y10= Product innovation, y11= Process innovation, y12= High growth, y13= Internationalization, and y14= Risk capital.[4]

Keep in mind that the GEI methodology applies the penalty for bottleneck (PFB) aggregation method that assumes that improvements in the weakest pillar produce the greatest impact in the analyzed system (Acs et al., 2014). Thus, the use of PFB-adjusted pillars in the BOD model would likely generate biased CI values (for illustrative purposes, the weighted (PFB) GEI scores are presented in Appendix 2). Because we are interested in computing CIs with relevant policy implications, the empirical application employs the equalized adjusted pillars—i.e., using equations (A3)-(A5) in Appendix 1 and without the PFB adjustment—to analyze the GEI. The analysis of different strategies that countries may follow to enhance their entrepreneurial ecosystem should necessarily be based on homogeneous (unbiased) data, which reinforces the use of the normalized values for the 14 GEI pillars. A similar approach has been adopted by empirical studies dealing with the analysis of CIs using raw, normalized data (e.g., Cherchye et al., 2007a; 2008; Sahoo et al., 2017).

4. Results: Composite indicator analysis of countries' entrepreneurial ecosystem

This section deals with the analysis of the results. Section 4.1 presents the baseline findings of the BOD-GEI. The empirical exercises in Sections 4.2 and 4.3 evaluate the responsiveness of countries' entrepreneurial ecosystem—measured by the BOD-GEI—to different ecosystem-enhancing strategies. We first analyze the variations in the BOD-GEI as a result of a quantity-led approach, based on the increase of the GEI, and of a quality-led strategy in which the extra resources are distributed among the top policy priorities identified by the BOD-GEI (Section 4.2). Second, Section 4.3 illustrates the case-specific implications of our model by showing how, relative to an alternative analytical method ('penalty of bottleneck'), the BOD-GEI can usefully reveal ecosystem-enhancing policies in three countries whose ecosystem presents important differences, in terms of level and configuration.

By using the event-study method, Section 4.4 evaluates the country-level effects—in terms of economic (GDP per capita) and entrepreneurial (venture capital investments) outcomes—of quality improvements in the entrepreneurial ecosystem. Finally, Section 4.5 presents the results of a series of tests evaluating the robustness and stability of the BOD-GEI to alternative model specifications. All models were estimated using the GAMS© software, and the code used to compute the CI scores and the weights is presented in Appendix 3.

4.1. Baseline results: Configuration of the entrepreneurial ecosystem and policy priorities

The summary results for the BOD-GEI scores and the ecosystem priorities—i.e., weights estimated via the BOD-GEI—are shown in Table 3 (Eq. (1)), while Appendix 4 presents the full matrix with the endogenous weights based on the BOD-GEI model. The findings show that countries prioritize different aspects of their entrepreneurial ecosystem. For example, for African countries the most relevant GEI pillars are start-up skills, which includes education and perceived skills variables, and process innovation included in the 'aspirations' sub-index (Table A1). These results are especially evident in Malawi and Tunisia. The development of both the education system and entrepreneurial skills would facilitate the exploitation of new business opportunities. The adoption of new technologies is a prerequisite for enhanced competitiveness. Support policies encouraging the use of newer technologies would arguably improve the entrepreneurial ecosystem by enhancing the technology base of the local fabric in these countries.

Table 3
Endogenous country-specific weights estimated via the 'benefit of the doubt' approach (BOD-GEI model).

GEI pillars (output set of BOD-GEI model)	Africa	America	Asia	Europe	Total
Y1: Opportunity Perception	0.0652	0.0668	0.0564	0.0843	0.0728
Y2: Startup Skills	**0.0969**	0.0789	**0.1124**	0.0648	0.0801
Y3: Risk Acceptance	0.0777	**0.0966**	0.0886	**0.0975**	0.0898
Y4: Networking	0.0738	0.0869	**0.1087**	**0.1373**	**0.1094**
Y5: Cultural Support	0.0776	0.0799	0.0946	0.0938	0.0875
Y6: Opportunity Startup	0.0868	**0.0948**	0.0942	0.0815	**0.0913**
Y7: Technology Absorption	0.0729	0.0825	0.0811	0.0850	0.0877
Y8: Human Capital	0.0848	0.0724	0.0669	0.0616	0.0691
Y9: Competition	0.0558	0.0736	0.0788	0.0783	0.0733
Y10: Product Innovation	0.0803	0.0804	0.0733	0.0949	0.0897
Y11: Process Innovation	**0.1082**	0.0901	0.0791	0.0850	0.0810
Y12: High Growth	0.0908	0.0838	0.0578	0.0611	0.0718
Y13: Internationalization	0.0793	0.0675	0.0824	0.0651	0.0703
Y14: Risk Capital	0.0753	0.0794	0.0673	0.0747	0.0751
Rank (max-min)	0.0652	0.0668	0.0564	0.0843	0.0728
Number of countries	12	19	9	31	71

Note: For each continent, bolded figures represent the two top-priority pillars.

The configuration of policy priorities among European countries is a second example worth analyzing. The findings reveal that policies that may produce superior quality improvements in the ecosystem relate to the 'risk acceptance' pillar (country risk and reduction of the social stigma of business failure) and the development of formal and informal networks that support business activity. It should be noted that these results are heterogeneous across Europe. For example: networks is the top priority for Finland and Netherlands; product innovation is the top GEI pillar for France, Germany, Italy and Sweden; whereas internationalization is the top pillar for various Eastern European countries (Czech Republic, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia) (Appendix 4).

Similarly, high country heterogeneity is reported in the Americas once we distinguish USA and Canada from Latin American countries. Network development, product innovation and technology absorption are the most important GEI pillar in the USA and Canada (Appendix 4). These pillars are strictly linked to connectivity, technology transfer processes and businesses' technological level, and they can be considered archetypal elements of the entrepreneurial ecosystem in developed economies. Among Latin American economies 'risk acceptance' (i.e., country risk and the social fear of failure) and 'opportunity startup' (opportunity-led entrepreneurship, instead of necessity-led entrepreneurship) are the two top GEI priorities. Argentina and Jamaica are examples of countries that should improve the 'risk acceptance' pillar—i.e., country risk and reduction of social fear of failure—whereas improvements in 'opportunity startup' factors are identified for Brazil, El Salvador and Panama.

The reported heterogeneity in the configuration of policy priorities is in line with our argument that the analysis of entrepreneurial ecosystems should account for countries' specific profile. Instead of promoting quantitative changes in the GEI, a tailor-made policy based on the information of our BOD-GEI model may prove itself effective in enhancing the quality of entrepreneurial ecosystems.

4.2. Assessment of countries' entrepreneurial ecosystem: Quantity- and quality-based strategies

This section evaluates how the quality of the entrepreneurial

[4] Notice that the analysis proposed in this study employs the 2017 version of the GEI index developed by Acs et al. (2017) which includes 14 pillars (the first version of the GEI index presented by Acs et al. (2014) includes a 'gender' pillar that was excluded from the GEI in subsequent versions of this composite indicator).

ecosystem improves as a result of a more informed policy. In computational terms, the empirical exercise presented in this section proposes a proportional allocation of additional resources—in our case, equivalent to 10 index points—to the two top-policy priorities identified by the BOD-GEI model (Eq. (1)). The resulting (new) output vector ($\boldsymbol{y}$= 1,…,14) was used to re-compute the CI scores (model BOD-2) and assess the value of the information provided by the BOD-GEI to improve the entrepreneurial ecosystem. Summary results of the two models (BOD-GEI and BOD-2) are presented in Table 4 (by continent and distinguishing between OECD and non-OECD countries), while Appendix 5 shows the breakdown of both the GEI scores and the CI values for the two models (BOD-GEI and BOD-2). For illustrative purposes, the table reports the quantitative change in the GEI after allocating additional resources, as well as the qualitative assessment of countries' ecosystem resulting from a directed strategy in which the extra resources are allocated proportionally to the two top priorities pinpointed by the BOD-GEI.

A good CI analysis should propose country-specific policies that produce qualitative changes in the entrepreneurial ecosystem. Results in Table 4 support this argument. An informed policy targeting specific pillars of the ecosystem produces a greater qualitative improvement than a policy focused on quantitative changes in the GEI. The mean BOD-GEI score is 0.4726 which means that, on average, the BOD-GEI might be expanded 52.74% (1–0.4726) (Table 4). The model identifies two (relatively) efficient countries with BOD-GEI = 1 (USA and Denmark). Africa shows the poorest results (mean BOD-GEI = 0.2665), while Europe is the most efficient continent (mean BOD-GEI = 0.6328).

In the case a country deploys additional resources a key question arising is what indicators should be expanded in order to optimize the entrepreneurial ecosystem. We argue that a policy focused on improving top priorities may represent an optimal strategy to enhance the quality of the ecosystem. Results for model BOD-2 show how a country-specific policy produces superior outcomes: based on the weights computed by the BOD-GEI, a strategy targeting priority components of the ecosystem produces a significant qualitative enhancement of 4.44% (Wilcoxon signed-rank test BOD-GEI vs. BOD-2: Z-value = 7.31 and p-value < 0.0000) (Table 4). Studies on entrepreneurial ecosystems stress that policy isomorphism is not efficient due to the differences in the forces shaping entrepreneurship across economies (Acs et al., 2014; Lafuente et al., 2020). Optimal policy should take into account the configuration of the local ecosystem. The analysis of the entrepreneurship policy in OECD viz.-à-viz. non-OECD countries constitutes a good example of this case (Table 4).

Among non-OECD economies 'opportunity perception' and 'human capital' are, on average, the strongest pillars of the ecosystem, and investments in these pillars would improve the BOD-GEI by 7.36%. The configuration of the GEI in these economies—i.e., low pillar values and few strong pillars—can partially explain this result. On contrary, among OECD countries the configuration of the ecosystem is dominated by a large number of high-performing pillars and few low-value pillars. For this group, investments in the two strongest pillars (on average, 'networking' and 'technology absorption') would generate a qualitative improvement of 3.29%, a value that almost triples the expected quantity change in the GEI if the additional resources are not strategically allocated.

4.3. Country-specific strategies to improve the entrepreneurial ecosystem

Thus far we have evaluated the ecosystem achievements in groups of countries and discussed the analytical advantages of the proposed BOD-GEI model (Sections 4.1 and 4.2). With these findings at hand, we now turn to the country-level calculations. Specifically, we briefly illustrate the changes in the ecosystem resulting from a policy based on the prescription of the BOD-GEI model in three countries with marked differences in terms of geography, economic activity, institutions, as well as the level and configuration of the entrepreneurial ecosystem: Sweden, Japan, and Costa Rica.

Results for the key parameters (weights) and the resulting BOD scores are presented in Table 5. To further corroborate the validity of the BOD-GEI, we contrast our estimations against an alternative approach based on the 'penalty of bottleneck' (POB[5]) aggregation model (Appendix 1), which assumes that weights are fixed (across countries) and homogeneous (i.e., $w = 1/14$ for all variables) and that investments in the weakest GEI pillars produce the greatest improvement (Acs et al., 2014).

Keep in mind that, similar to Section 4.2, the comparison between the BOD-GEI and the POB results is based on a hypothetical situation in which countries proportionally allocate extra resources (i.e., 10 index points) among the policy priorities identified by each model: the two top-pillars in the case of the BOD-GEI, and the two bottleneck pillars in the case of the POB approach.

Sweden, the high-quality ecosystem case in this analysis, has a relatively balanced configuration of the GEI pillars, which ranges between 52.26 ('startup skills') and 97.60 ('opportunity startup'). In computational terms, this vector is included in the data matrix used to solve the linear program in Eq. (1) (BOD-GEI). The endogenous weights and 'pie shares' needed to compute the BOD-GEI are presented in column 2 of Table 5. Notice that the BOD-GEI is the weighted sum of the rescaled 'pie shares' (Eq. (1):$\sum_{j=1}^{14} w_{ij} y_{ij}$). Taking into account the assumptions of the BOD-GEI, a quick glance at the weights reveals that 'product innovation' (y10) and 'networking' (y4) are the key pillars shaping Sweden's ecosystem. A directed policy targeting these aspects (i.e., proportional allocation of 10 index points) translates into a qualitative improvement of 3.10% in the entrepreneurial ecosystem (Table 5: BOD-GEI = 0.9192 and BOD-2 = 0.9477). From a policy perspective, examples of actions that Swedish policy makers can take in this direction include the development and commercialization of research advancements as well as university-industry collaborations ('product innovation'), or the promotion of networks connecting actual and potential entrepreneurs ('networking').

For ease of comparability, we evaluate the estimations of the BOD-GEI viz.-à-viz. the results produced by the POB aggregation method. In this case, 'startup skills' (y2) and 'high growth' (y12) are the bottleneck pillars. By using the procedure described in Appendix 1 to compute the POB-adjusted GEI we observe that, if policy makers invest in the two bottlenecks the ecosystem would improve by 2.26% (POB-adjusted GEI = 74.10 and post-investment POB-adjusted GEI = 75.77).

For Japan, the results (weights) of the BOD-GEI indicate that 'networking' (y4) and 'risk capital' (y14) are the main pillars of the country's entrepreneurial ecosystem (Table 5). Again, if additional resources are proportionally allocated among these pillars, the quality of the local ecosystem would improve by 7.07% (Table 5: BOD-GEI = 0.6411 and BOD-2 = 0.6864). Similar to the Swedish case, the 'networking' pillar can be enhanced by stimulating entrepreneurial networks, while reforms that encourage the involvement of business angels in entrepreneurial processes is an example of a policy that can improve the 'risk capital' pillar. Japan's ecosystem presents a more unbalanced configuration with two clear bottlenecks ('opportunity perception' and 'startup skills'). If a policy based on the POB method is adopted to proportionally allocate additional resources among these pillars, the GEI would improve by 4.95% (POB-adjusted GEI = 50.11 and post-investment POB-adjusted GEI = 52.59).

Concerning the third country example, Costa Rica has a weak ecosystem with many low-value (bottleneck) pillars and few strong

[5] Following the approach by Acs et al. (2014, p. 484), the 'penalty of bottleneck' (POB) function used to estimate the adjusted GEI pillar values (y_{ij}) is $h_{ij} = \min y_i + (1 - e^{-(y_{ij} - \min y_i)})$ (see equation (A6)). The resulting GEI pillar values are introduced in equation (A7) to obtain the POB-adjusted GEI scores. The full description of the GEI methodology and the POB aggregation method are presented in Appendix 1.

Table 4
GEI performance assessment after improving (in 10 index points) the observed weakest pillar and the two top country-specific priority pillars (weights) derived from the BOD model (BOD-GEI).

	1) Quantity improvement in the GEI index (normalized values)			2) Quality improvement in the GEI index (normalized values)		
				BOD-GEI model (Eq. (1))	BOD-2: pillar values after improving the two top priority pillars	
	Observed GEI index	GEI score after improving 10 index points	Variation	GEI performance	GEI performance	Variation
Panel A: Continents						
Africa (12 countries)	26.69	27.51	3.07%	0.2665	0.2856	7.16%
Americas (19 countries)	33.95	34.74	2.35%	0.3719	0.3958	6.42%
Asia (9 countries)	41.15	41.97	1.97%	0.4080	0.4377	7.29%
Europe (31 countries)	54.08	54.86	1.42%	0.6328	0.6570	3.83%
Total	**42.43**	**43.28**	**2.02%**	**0.4726**	**0.4936**	**4.44%**
Panel B: OECD vs. non-OECD countries						
OECD countries (32 countries)	59.02	59.76	1.26%	0.6946	0.7174	3.29%
Non-OECD countries (39 countries)	28.81	29.57	2.64%	0.2904	0.3118	7.36%
Total	**42.43**	**43.28**	**2.02%**	**0.4726**	**0.4936**	**4.44%**

Note: The quantity-based analysis of the GEI index compares the GEI values after improving the countries' score by 10 index points. The quality-based analysis is based on a set of BOD models that use the 14 GEI pillars as outputs (Eq. (1)): a) the main BOD model (BOD-GEI) uses the observed GEI pillar values for 2016 as outputs, b) For the second model (BOD-2), the output values (GEI pillars for 2016) are adjusted by allocating the 10 index points proportionally to the two top-priority pillars (country-specific priority pillars) computed in model 1 (BOD-GEI).

Table 5
BOD results: Improvements in the entrepreneurial ecosystem for the selected countries.

GEI pillars (output set)	1) Sweden			2) Japan			3) Costa Rica		
	GEI pillars	BOD-GEI 'pie shares' (weight)	BOD-2 'pie shares' (weight)	GEI pillars	BOD-GEI 'pie shares' (weight)	BOD-2 'pie shares' (weight)	GEI pillars	BOD-GEI 'pie shares' (weight)	BOD-2 'pie shares' (weight)
Y1: Opportunity Perception	95.90	0.0806 (0.084)	0.0815 (0.085)	17.56	0.0125 (0.071)	0.0125 (0.071)	41.36	0.0347 (0.084)	0.0347 (0.084)
Y2: Startup Skills	52.26	0.0162 (0.031)	0.0167 (0.032)	14.22	0.0107 (0.075)	0.0108 (0.076)	73.71	0.0346 (0.047)	0.0361 (0.049)
Y3: Risk Acceptance	70.40	0.0753 (0.107)	0.0711 (0.101)	64.96	0.0487 (0.075)	0.0494 (0.076)	33.29	0.0346 (0.104)	0.0350 (0.105)
Y4: Networking	73.99	0.0851 (0.115)	0.0908 (0.115)	32.48	0.0637 (0.196)	0.0742 (0.198)	40.31	0.0306 (0.076)	0.0351 (0.087)
Y5: Cultural Support	88.81	0.0826 (0.093)	0.0835 (0.094)	38.84	0.0128 (0.033)	0.0132 (0.034)	45.21	0.0303 (0.067)	0.0346 (0.069)
Y6: Opportunity Startup	97.60	0.0791 (0.081)	0.0839 (0.086)	60.10	0.0559 (0.093)	0.0571 (0.095)	31.83	0.0347 (0.109)	0.0350 (0.110)
Y7: Technology Absorption	94.57	0.0794 (0.084)	0.0804 (0.085)	96.90	0.0601 (0.062)	0.0601 (0.062)	17.85	0.0059 (0.033)	0.0070 (0.039)
Y8: Human Capital	64.40	0.0188 (0.029)	0.0187 (0.029)	95.94	0.0528 (0.055)	0.0556 (0.058)	22.38	0.0186 (0.083)	0.0208 (0.093)
Y9: Competition	86.88	0.0834 (0.096)	0.0930 (0.107)	56.48	0.0395 (0.070)	0.0395 (0.070)	42.38	0.0348 (0.082)	0.0351 (0.074)
Y10: Product Innovation	66.55	0.0839 (0.126)	0.0909 (0.127)	95.93	0.0700 (0.073)	0.0767 (0.080)	28.02	0.0347 (0.124)	0.0350 (0.125)
Y11: Process Innovation	89.88	0.0764 (0.085)	0.0773 (0.086)	97.65	0.0537 (0.055)	0.0596 (0.061)	31.35	0.0345 (0.110)	0.0348 (0.111)
Y12: High Growth	55.69	0.0162 (0.029)	0.0167 (0.030)	97.65	0.0537 (0.055)	0.0596 (0.061)	28.72	0.0348 (0.121)	0.0348 (0.121)
Y13: Internationalization	81.64	0.0833 (0.102)	0.0841 (0.103)	59.99	0.0456 (0.076)	0.0498 (0.083)	22.08	0.0068 (0.031)	0.0071 (0.032)
Y14: Risk Capital	72.07	0.0591 (0.082)	0.0591 (0.082)	55.35	0.0614 (0.111)	0.0682 (0.113)	18.81	0.0070 (0.037)	0.0077 (0.041)
GEI score	77.89			63.15			34.09		
BOD-GEI model		0.9192			0.6411			0.3766	
BOD-2 model			0.9477			0.6864			0.3927
Percentage improvement			3.10%			7.07%			4.27%

Note: The weights used to compute the BOD-GEI score (Eq. (1)) are presented in Appendix 4, while results for the BOD-2 model emerge from re-computing the BOD-GEI model after additional resources (10 index points) are proportionally distributed to the two-top policy priorities, based on the weights estimated in model BOD-GEI. For both models (BOD-GEI and BOD-2) the CI value equals the sum of the country's 'pie shares' (Eq. (1): $\sum_{j=1}^{14} w_{ij} y_{ij}$).

factors. Based on Eq. (1), 'product innovation' (y10) and 'high growth' (y12) are the key drivers of Costa Rica's ecosystem. By replicating the resource allocation exercise used in this section, a proportional increase in the 'product innovation' and 'high growth' pillars would enhance the country's ecosystem by 4.27% (Table 5: BOD-GEI = 0.3766 and BOD-2 = 0.3927). As mentioned above, from a policy viewpoint improvements in the 'product innovation' pillar can be achieved by embracing specialized policies promoting investments in research centers as well as university-industry collaborations, whereas the 'high growth' pillar can be enhanced by introducing reforms that boost the economic activity and employment level of new and incumbent businesses. On contrary, if policy design is based on the POB method, 'technology absorption' (y7) and 'risk capital' (y14) should be prioritized. By computing the POB-adjusted GEI values (Appendix 1), investments in these bottlenecks would enhance the country's ecosystem by 3.89% (POB-adjusted GEI = 32.07 and post-investment POB-adjusted GEI = 33.31).

Overall, the results of this comparative exercise show how a directed policy that follows the prescription of our BOD-GEI model outperforms the policy logic based on of the POB method.

In sum, the analysis presented in this section leads to conclude that policy design based on more informed models, such as the BOD-GEI, that account for the configuration of the local ecosystem and territorial heterogeneity constitutes an ideal scenario for policy makers. The proposed analytical tool for identifying optimal entrepreneurship policy may offer valuable guidance to countries on how to use additional resources in order to maximize the quality of their entrepreneurial ecosystem.

4.4. Entrepreneurial ecosystem and national outcomes

This section presents the results of the analysis linking variations in the entrepreneurial ecosystem and changes in national outcomes. Because entrepreneurial ecosystems are not a list of independent tasks that would produce immediate results if completed, the analysis of the connection between entrepreneurial ecosystems and national outcomes using regression models may offer inconclusive findings. Nevertheless, relevant insights can be generated by studying how the economy reacts to variations in the entrepreneurial ecosystem. Therefore, we employ standard event-study method to evaluate changes in economic (GDP per capita) and entrepreneurial (venture capital investments) outcomes during the seven-year period centered on the state of the entrepreneurial ecosystem in the focal study year (2016), that is, for the period 2012–2019.

Concerning the design of this analysis, three considerations are in order. First, we consider the average annual change of two variables related to different country outcomes: the economic outcome is GDP per capita at 2017 prices of PPP international dollars (e.g., Lafuente et al., 2020), while venture capital investments in early-stage and established firms as a proportion of GDP is used to capture entrepreneurship outcomes (e.g., Drover et al., 2017; Basu et al., 2011). Note that GDP data is available for the full sample from the World Bank (https://data.worldbank.org), while information on venture capital investments is only available for 28 OECD countries (https://stats.oecd.org).

Second, to examine countries' performance trajectory before and after 2016, we ran the BOD-GEI model (Eq. (1)) on the 2012 data, and results were used to categorize the entrepreneurial ecosystem in 2016: 'countries with matched priorities' reporting a change in the entrepreneurial ecosystem in 2016 that is aligned with the policy priorities identified in 2012 (change in the top or the two top GEI pillars); and 'countries without matched priorities' whose change in the entrepreneurial ecosystem in 2016 is not aligned with the strategy suggested by the BOD-GEI model in 2012.[6]

Third, to accurately evaluate performance changes we corrected for potential problems related to mean reversion of performance time-series. We thus report the average annual changes in national outcomes for two time windows: from year –3 to year –1 (2013–2015), and from year –1 to year +3 (2015–2019). This approach has been widely used in prior work using event studies to assess executive turnovers (e.g., Epure and Lafuente, 2015; Huson et al., 2004), innovation (e.g., Borah and Tellis, 2014; Sood and Tellis, 2009), and country-level phenomena (e.g., Johannesen and Larsen, 2016).

We are aware that the criteria used to identify the state of the entrepreneurial ecosystem among the sampled countries as well as the selected time window are somewhat arbitrary. In our view, this analysis constitutes solid and valuable evidence by unveiling how the economy responds to more or less directed changes in the entrepreneurial ecosystem. Table 6 presents the descriptive statistics (values in levels) as well as the results of the analysis (average performance changes) for the two groups of countries ('countries with matched priorities' and 'countries without matched priorities'). In the table Panels A and B show the results for the GDP per capita (economic outcome), while the findings for venture capital investments (entrepreneurial outcome) are presented in Panels C and D.

Additionally, Figs. 2 and 3 present a complementary descriptive analysis by correlating the BOD-GEI and the GEI with the two studied outcomes. For illustrative purposes, notice that in the figures we use the CI values for 2016 (BOD-GEI and GEI) whereas national outcomes are measured as the average values between 2015 and 2019.[7] Overall, the findings in Fig. 2 show a strong positive correlation between both ecosystem variables (BOD-GEI and GEI) and mean GDP per capita. In the case of Fig. 3, we observe a slightly greater correlation (and the fit of the slope) between the BOD-GEI and average venture capital investments (as% of GDP) (Bivariate correlation: 0.6983 and p-value < 0.000), compared to that reported for the GEI (Bivariate correlation: 0.6320 and p-value < 0.000).

A first result worth highlighting is the diversity within the two groups of countries ('countries with matched priorities' and 'countries without matched priorities'). This suggests that improvements in the entrepreneurial ecosystem—whether they are based on policy priorities identified in 2012 or not—are not conditioned by countries' development level. When GDP per capita is the outcome variable, the group of 'countries with matched priorities' includes 20 countries: four African states (Algeria, Botswana, Ghana and South Africa), three American states (Barbados, Costa Rica and USA), four Asian states (China, Japan, Singapore and South Korea); and nine European countries (Estonia, Finland, Germany, Ireland, Netherlands, Norway, Slovenia, Sweden and Switzerland). In the case of the venture capital investments this group narrows down to 12 countries: Estonia, Finland, Germany, Ireland, Japan, Netherlands, Norway, Slovenia, South Korea, Sweden, Switzerland and USA.

Results for the full sample in Panel A show that most countries increased their GDP per capita between the two analyzed periods. However, it was found that the average growth rates observed for the period 2013–2015 are not significantly different from those observed for the period 2015–2019 (Panel B). This is due to the high of proportion of countries reporting a lower growth rate in GDP per capital during 2015–2019, compared to figures reported in the 2013–2015 period (Table 6).

The findings for the entrepreneurial outcome show that, for the full sample, venture capital investments represented 4.27% of the GDP in the 2013–2015 period, and that this proportion significantly grew to 6.05% in the 2015–2019 (Table 6: Panel C). Although this result is

[6] From the comparison of the BOD-GEI model for 2012 and 2016, a total number of 20 countries (fully or partially) followed the improvement strategy suggested by the BOD-GEI model in 2012. Singapore is the only country that reported an (intended or unintended) improvement in the two top policy priorities (GEI pillars) identified in 2012 (technology absorption and risk capital). Nineteen countries partially followed the policy strategy identified by the BOD-GEI in 2012 (again, the identified shift in the entrepreneurial ecosystem among these countries was intended or unintended).

[7] In unreported results, available on request, we found a strong regularity in the descriptive results emerging from alternative specifications correlating both CIs for 2016 (BOD-GEI and GEI) with other outcome values based on 2016 and 2019 data. In both scatterplots, notice that we use the mean outcome values for the 2015-2019 period in order to present an analysis that is consistent with the tenor of the argument line of Section 4.4.

Table 6
Performance comparisons during 2013–2019 between countries that prioritized GEI pillars (matched priorities) and countries that did not prioritize GEI pillars (unmatched priorities) in 2016.

	Period: –3 to –1 (2013–2015)	Period: –1 to +3 (2015–2019)	Wilcoxon signed-rank test
Panel A: level of GDP per capita (71 countries)			
Total (71 countries)	26,560.06	28,200.30	6.234*** (62: 9)
Countries with matched priorities (20 countries)	38,139.33	40,898.89	3.845*** (19: 1)
Countries with unmatched priorities (51 countries)	22,019.18	23,220.40	4.846*** (43: 8)
Panel B: mean% change in GDP per capita (71 countries)			
Total (71 countries)	0.0190	0.0172	–0.195 (37: 34)
Countries with matched priorities (20 countries)	0.0210	0.0213	0.224 (11: 9)
Countries with unmatched priorities (51 countries)	0.0182	0.0165	–0.384 (26: 25)
Panel C: level of venture capital investments (% of GDP) (28 OECD countries)			
Total (28 countries)	0.0427	0.0605	3.689*** (24: 4)
Countries with matched priorities (12 countries)	0.0640	0.0904	2.981*** (11: 1)
Countries with unmatched priorities (16 countries)	0.0267	0.0381	2.275** (13: 3)
Panel D: mean% change in venture capital investments (% of GDP) (28 OECD countries)			
Total (28 countries)	0.1760	0.2117	1.412 (19: 9)
Countries with matched priorities (12 countries)	0.1523	0.2457	1.961** (10: 2)
Countries with unmatched priorities (16 countries)	0.1938	0.1862	–0.455 (9: 7)

Note: The table presents the performance comparisons of levels and average annual changes between 2013 and 2019. Results are reported for four measures: level and average annual change of GDP per capita at 2017 prices of PPP international dollars (data for the full sample obtained from the World Bank: https://data.worldbank.org); and level and average annual change in venture capital investments, expressed as a percentage of GDP (data for 28 OECD countries obtained from the OECD: https://stats.oecd.org). Data on venture capital investments is not available for Chile, Israel, Mexico, and Turkey. Results are reported for two distinct periods centered on the study's focal year of analysis (2016): period –3 to –1 (2013–2015) and period –1 to +3 (2015–2019). The BOD-GEI model (Eq. (1)) was applied on the GEI 2012 data in order to identify, for each country, the two top policy priorities (weights), and the direct comparison between the two top GEI pillars identified for 2012 and the two GEI pillars with the greatest improvement in 2016 was made to verify countries' GEI prioritization policy, based on the prescription identified in 2012. Note that, the prioritization of one or the two top GEI pillars is the criterion used to identify countries that followed the policy prescription proposed in 2012 (i.e., countries with matched priorities). The number of countries with positive and negative performance changes are presented in brackets (i.e., figures should be read as "countries with positive changes": "countries with negative changes"). The Wilcoxon signed-rank test was used for the inter-temporal performance comparisons (period –3 to –1 vs. period –1 to –3). *, **, *** indicates significance at the 10%, 5% and 1%, respectively.

consistent for both groups of countries, the level of venture capital investments is higher among 'country with matched priorities'. For the period 2015–2019 examples of high venture capital investment rates are reported in the USA (51.191%), Canada (15.72%), and South Korea (10.27%). Also, Slovenia is the only 'country with matched priorities' that reduced its venture capital investments (as a proportion of GDP) between the two periods. Among 'countries without matched priorities', Czech Republic, Latvia and Lithuania report a fall in the level of venture capital investments. Concerning changes in venture capital investments, results in Panel D reveal that the average annual variation in this entrepreneurial outcome increased from 17.60% (period 2013–2015) to 21.17% (period 2015–2019); however, this finding is not significant mostly because the mean annual rate of venture capital investments has fallen in nine countries: Austria, Hungary, Latvia, Lithuania, Poland, Portugal, Slovenia, Spain, and USA.

Additionally, results underline the value of a solid entrepreneurial ecosystem. We observe that the mean annual change in venture capital investments significantly increased only for the group of 'countries with matched priorities' whose improvement in the entrepreneurial ecosystem in 2016 is in line with the prioritization strategy identified in 2012. For the group of 'countries without matched priorities' the cross-period comparison is not significant because seven countries (out of 16) show a lower annual change in venture capital investments during 2015–2019 than in the 2013–2015 period (Austria, Hungary, Latvia, Lithuania, Poland, Portugal, and Spain).

Overall, two main results can be extracted from the analysis presented in this section. On the one hand, the alignment between policy priorities and quality improvements in the entrepreneurial ecosystem is not exclusive domain of developed economies, regardless of whether such changes are planned or not. On the other hand, the results suggest that quality improvements in the entrepreneurial ecosystem pay off. Perhaps the complexity and diversity of the items included in macro figures (e.g., GDP) explain the often inconclusive results linking economic outcomes and the entrepreneurial ecosystem reported in prior studies. But, when we look at outcomes more directly connected to the entrepreneurial ecosystem (e.g., venture capital investments) a much clearer picture emerges, and it was possible to identify a positive correlation between quality improvements in the entrepreneurial ecosystem—based on the assumptions of the BOD-GEI—and entrepreneurship-related outcomes.

4.5. Robustness checks

This section presents the results of a number of robustness checks evaluating the suitability of the proposed BOD-GEI model compared to alterative specifications in which weights are computed via a 'full flexibility' BOD model (BOD-F) and principal component analysis (BOD-PCA). We also present the findings of a simple uncertainty analysis evaluating the potential effect of the different weighting methods on the ranking of countries based on CI scores. Finally, we evaluate the sensitivity of the BOD-GEI scores to different 'pie share' intervals.

Full flexibility BOD model.—We first verified if a BOD model that allows full flexibility of the weights offers empirical findings comparable to those reported in Section 4.1 (BOD-GEI). To achieve this, we removed the 'pie share' restriction from the linear model presented Eq. (1) and re-computed both the CI scores and the pillar weights. The results in Appendix 6 indicate that the CI scores significantly increase in the 'full flexibility' BOD model (BOD-F), compared to the results reported in Table 4 (Wilcoxon signed-rank test BOD-F vs. BOD-GEI: Z-value = 7.31 and *p*-value < 0.0000). We also observe that countries prioritize on average 2.44 GEI pillars (ranging between 1 and 6). African countries report the lowest number of priority pillars (2.25); however, a further scrutiny of the data reveals some differences: Tunisia prioritizes four

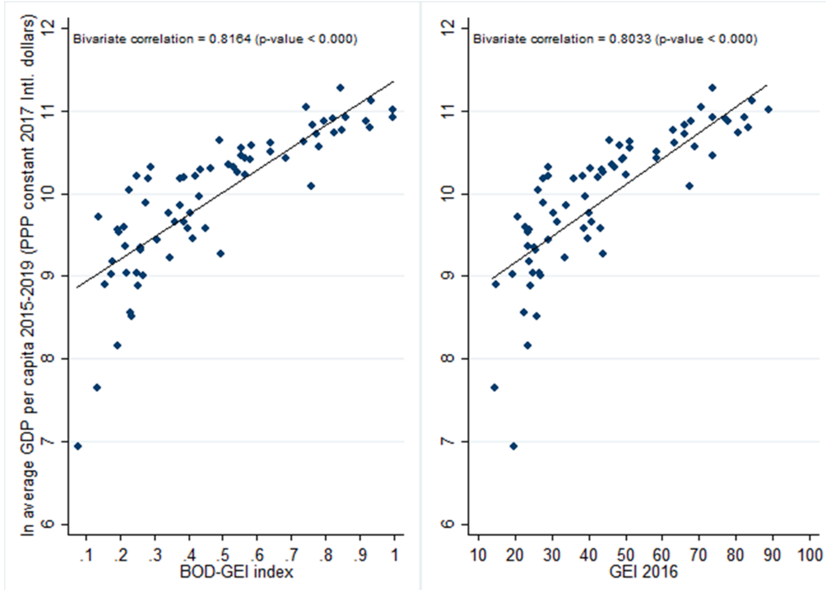

Fig. 2. The relationship between the BOD-GEI, the GEI and GDP per capita. Number of observations: 71 countries. BOD-GEI scores are obtained from Eq. (1), whereas data on the GEI values and the logged GDP per capita (expressed at 2017 prices in PPP, constant international dollars) were obtained from The Global Entrepreneurship Development Institute and the World Bank, respectively.

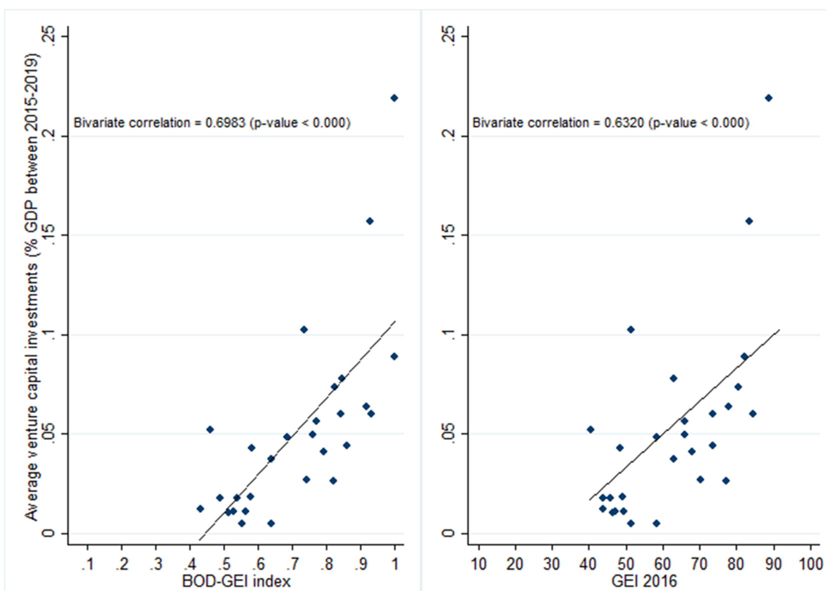

Fig. 3. The relationship between the BOD-GEI, the GEI and venture capital investment (% of GDP). Number of observations: 28 countries. BOD-GEI scores are obtained from Eq. (1), whereas data on the GEI values and the venture capital investments (as% of GDP) were obtained from The Global Entrepreneurship Development Institute and the OECD databases, respectively.

pillars, while a group of four countries (Angola, Botswana, Malawi, and Nigeria) give relevance to three pillars. On contrary, European countries prioritize the greatest number of GEI pillars (2.56), and in this group 14 countries prioritize one pillar, two pillars are relevant for Sweden, seven countries assign a positive weight to three pillars, five countries prioritize four pillars, three countries give relevance to five pillars (France, Switzerland, and UK), while Estonia prioritizes the highest number of GEI pillars (6). For American economies, seven countries assign a positive weight to one pillar (including the US), while Jamaica prioritizes the highest number of pillars (5). In Asia, China, Korea and Singapore prioritize four GEI pillars.

The 'full flexibility' BOD model considers the possibility that countries ignore pillars on which they perform relatively poor. The results indicate that this model (BOD-F) partially captures the performance of the GEI. Furthermore, the findings of this test corroborate that our main model presented in Eq. (1) (BOD-GEI) is a more realistic approach to generate valuable information on policy priorities that can be used to produce quality improvements in the entrepreneurial ecosystem.

Weights computed via principal component analysis (PCA).—Second, we dealt with the possibility that a weight matrix generated via principal component analysis (PCA) offers valuable information that can be used for policy purposes. We computed a PCA model using the 14 GEI pillars as inputs. The first component extracted from the PCA model explains

59.62% of the total variance (eigenvalue = 8.3475), and the average correlation between this component and the GEI pillars is 0.7665 (ranging between 0.5615 and 0.9206). The resulting values (eigenvectors) were used to assign the weight to each pillar: Opportunity perception (Y1) = 0.0675, Startup skills (Y2) = 0.0571, Risk acceptance (Y3) = 0.0774, Networking (Y4) = 0.0523, Cultural support (Y5) = 0.0767, Opportunity startup (Y6) = 0.0858, Technology absorption (Y7) = 0.0818, Human capital (Y8) = 0.0695, Competition (Y9) = 0.0721, Product innovation (Y10) = 0.0701, Process innovation (Y11) = 0.0767, High growth (Y12) = 0.0672, Internationalization (Y13) = 0.0680, and Risk capital (Y14) = 0.0776.

The results presented in Appendix 7 indicate that average CI value is 59.11% (1–0.4089), a value that is similar to that obtained in the BOD-GEI model (mean BOD-GEI score = 0.4726). Additionally, we observe that our main BOD model (BOD-GEI) and the model based on the PCA (BOD-PCA) produce a similar set of priority pillars. On average, the BOD-GEI model identifies 'Start-up skills' and 'Process innovation' as the top priority pillars for African countries (Table 3), while the greatest weights computed by the BOD-PCA model are assigned to 'Start-up skills' and 'Technology absorption' (Appendix 7: 'Process innovation' is the fourth ranked pillar). For American and Asian economies, both models (BOD-GEI and BOD-PCA) highlight the same priority pillars: 'Process innovation' and 'Risk acceptance' for America, and 'Technology Absorption' and 'Startup skills' for Asia. According to the results of the BOD-GEI model (Eq. (1)), the most important GEI pillars among European countries are 'Risk acceptance' and 'Networking'. In the model that uses the theoretical weights computed via PCA (BOD-PCA) 'Risk acceptance' is again the top priority pillar of the entrepreneurial ecosystem, but 'Networking' is the tenth pillar, in terms of relevance (Appendix 7: 'Opportunity perception' is the second priority pillar).

Finally, notice the results of the BOD-PCA model corroborate the configuration structure of countries' entrepreneurial ecosystem reported by our main model (BOD-GEI). The findings in Appendix 7 show that the configuration of the entrepreneurial ecosystem—in terms of GEI pillars— in less developed economies is characterized by several low value pillars (few strong pillars). In our sample, this is especially evident in Africa and Asia. On contrary, among European countries the configuration of the entrepreneurial ecosystem is more balanced and dominated by a large number of high-performing pillars and few low-performing pillars.

Uncertainty analysis for CI scores (comparison of CIs resulting from different weighting methods).—A number of factors can affect the results of a CI analysis (see, e.g., Cherchye et al., 2008). In this study, two potential sources of uncertainty are analyzed: the changes in the raw data as a result of different improvement strategies of the entrepreneurial ecosystem (GEI), and the different weighting methods used to compute the countries' CI scores. Therefore, the third robustness check analyzes the potential effect of these two factors on the interpretations of the countries' CI scores (BOD-GEI: weights using the 'pie share' restriction, BOD-2: improvement in the two top priority pillars, and BOD-PCA: estimation using weights computed via principal components analysis). Based on the three different CI estimations, the results of this uncertainty analysis are presented in Appendix 8 (Figures A1, A2 and A3). In the figures, whisker plots show the median as well as the minimum and the maximum value of the CI scores. For interpretation purposes, an overlap of the whisker plots for a group of countries suggests that their CI scores and, consequently, their ranks are similar. On contrary, if the whisker plots for a group of countries do not overlap, then CI estimations are robust and independent of the two potential sources of uncertainty analyzed in the study.

The findings indicate that the two sources of uncertainty analyzed in the study do not have a significant impact on the interpretation of the CI scores. The results indicate that the US, Denmark, Switzerland and Canada are consistently the countries with the highest CI scores. Nevertheless, there is a relatively small group of countries whose CI value is influenced by the assumptions of the BOD models: Israel, Japan, Singapore and Malaysia (Figure A1 in Appendix 8). Among top performing countries, the results in Figure A2 (Appendix 8) show that the performance of most countries in this group can be clearly distinguished, with the exception of two groups of countries with similar CI levels: Finland, Germany and Austria on the one hand; and Chile and Israel on the other hand. Finally, note that the influence of the model assumptions becomes more evident among countries with a poor performing CI (Figure A3 in Appendix 8). In this case, examples of notable variations in CI values are Argentina, Bosnia, Brazil, Ecuador, El Salvador and Iran.

Sensitivity analysis of CI scores to different 'pie share' bandwidths.—The last robustness check deals with the sensitivity of CI scores. Specifically, we ran different BOD-GEI specifications (Eq. (1)) using multiple weight estimation criteria in order to verify if changes in the weight intervals produce uncertain results due to rank reversal. For analytical purposes, the lower (L_j) and upper (U_j) bound of the 'pie share' constraint in Eq. (1) were modified to compute a new set of BOD-GEI scores using the following weight interval criteria: A) 5%: $L_j = (1/14) \times 0.05 \wedge U_j = (1/14) \times 1.05$, B) 10%: $L_j = (1/14) \times 0.10 \wedge U_j = (1/14) \times 1.10$, C) 35%: $L_j = (1/14) \times 0.35 \wedge U_j = (1/14) \times 1.35$, and D) 50%: $L_j = (1/14) \times 0.50 \wedge U_j = (1/14) \times 1.50$. These weight configurations are compared to the findings obtained for the main BOD-GEI model. Results of the analysis are presented in Figure A4 of Appendix 9. Similar to the uncertainty analysis described above, the whisker plot shows the median as well as the minimum and the maximum value of the different CI scores. From Figure A4 we observe that changes in the weight intervals do not cause serious rank reversal problems. Examples of countries reporting large changes in BOD-GEI values as a result of using different weight intervals are Chile, Norway, Japan, and Singapore. These findings indicate that the proposed BOD-GEI to measure countries' entrepreneurial ecosystem are stable to different models specifications—in terms of weight intervals—which corroborates the reliability of the results presented throughout Section 4.

Overall, the objective of the various analyses presented in this section was to show that the estimation strategy adopted to generate the main findings of this study is robust to alternative improvement strategies and weighting approaches. The core finding of these robustness checks further validate the interpretations of the BOD-GEI model presented in Sections 4.1-4.4.

5. Concluding remarks, implications and future research lines

5.1. Concluding remarks

We started this research with the objective of evaluating the quality of entrepreneurial ecosystems across countries with distinct characteristics. Entrepreneurial ecosystems are not checklists. In this sense, CIs have been invoked as a valuable tool—out of many available in the economists' toolkit—to assess multidimensional economic phenomena, such as entrepreneurial ecosystems. Despite the apparent simplicity of our CI analysis, we believe that our empirical work is a useful exercise.

This study has produced evidence on the importance of computing endogenous, country-specific policy priorities for optimal policy design aimed at enhancing countries' entrepreneurial ecosystem. More concretely, we scrutinized how objective weights estimated via the 'benefit of the doubt' (BOD) model can offer insightful information to policy makers. We argue that CI analyses should go beyond canonical rankings and homogeneous prescription, and promote the generation of valuable information that equips policy makers with the means for developing tailor-made entrepreneurship policy.

Overall, the findings are consistent with the view that an analysis based on the BOD approach provides relevant information to identify priority dimensions of the entrepreneurial ecosystem. Instead of quantity variations and basic rankings, we show how quality improvements in this ecosystem can be realized by deploying additional resources among the policy priorities identified by the non-arbitrary, informed criteria of the BOD-GEI model. Results of the analysis connecting changes in the BOD-GEI and national outcomes validate this argument. We found a positive response by venture capitalists to quality improvements in countries' entrepreneurial ecosystem. Macroeconomic figures, such as GDP, result from different processes carried out by multiple actors, which can explain why we did not find a convincing link between economic growth and changes in the ecosystem. The key findings clearly indicate that entrepreneurial ecosystems can eventually boost venture capitalists' activity, thus suggesting that entrepreneurship policy should be evaluated on the basis of its impact on outcomes more directly connected to entrepreneurship.

5.2. Policy implications

The findings of this study have relevant policy implications. The primary policy recommendation that can be drawn from our results is clear: a tailor-made, more informed policy accounting for the properties of the local entrepreneurial ecosystem seems more appropriate than homogeneous actions based on policy isomorphism. This key aspect is connected to our first research question ('how would the quality analysis of entrepreneurial ecosystems based on CIs differ when endogenous weights capturing countries' heterogeneity are included in the model?'). One of the main challenges for policy makers is to choose accurate entrepreneurship variables to generate economically meaningful policies. During the last two decades scholars have witnessed a drastic change in the way to analyze entrepreneurship at country level, which has shifted from a narrow view based on the links between business formation rates and economic figures (Naudé, 2011; Van Stel et al., 2005) towards a more holistic approach where the entrepreneurial ecosystem is at the heart of the analysis (Acs et al., 2014, 2016; Autio et al., 2015; Lafuente et al., 2020). In this sense, we argue that the many dimensions of the ecosystem included in the Global Entrepreneurship Index (GEI) and its connection to economic figures validate this metric to measure entrepreneurship as a national phenomenon.

Second, in a related manner, our analysis shows how the BOD model can be instrumental for the identification of country-specific policy priorities. In contexts of insufficient information about the relative importance of the variables shaping the entrepreneurial ecosystem, the BOD model constitutes an alternative method to evaluate CIs and reduce the uncertainty that often questions their validity (Cherchye et al., 2008; Lafuente et al., 2020). In the specific case of the BOD-GEI, the computation of endogenous (country-specific) weights can prove itself effective to identify priorities that can become the target of a more informed entrepreneurship policy (Acs et al., 2014).

The characteristics of the entrepreneurial ecosystem—which affect the outcomes of entrepreneurial action (Acs et al., 2014)—can be described and improved. Nevertheless, policy makers often lack reliable data to know how to improve the entrepreneurial ecosystem, which might translate into discretionary or ambiguous behaviors by policy makers that materialize in reforms that produce mere quantitative increases of the entrepreneurial activity with limited economic impact (Lafuente et al., 2020). The use of analytical tools—such as the proposed BOD-GEI model—has the potential to reduce the ambiguity or the discretionary behavior of policy makers, as well as to identify the specific components of the entrepreneurial ecosystem that should be prioritized in order to produce a directed policy that induces the fertilization of the entrepreneurial ecosystem with a long term perspective.

Third, in relation to our second research question ('does an analysis of entrepreneurial ecosystems based on CIs help to unveil economically meaningful policies which can impact relevant country-level outcomes?'), the findings highlight the value of the BOD-GEI model for impactful policy making. In the case the targeted outcome is the entrepreneurial ecosystem itself, we found that the effectiveness of entrepreneurship policy is conditional on the configuration of the local ecosystem. For developing countries whose ecosystem is characterized by few strong pillars, policy interventions will likely be more productive if resources are devoted to specific aspects of the entrepreneurial ecosystem. This effect is less pronounced among developed countries whose entrepreneurial ecosystem is more balanced, in terms of GEI pillars. This leads to conjecture that effective policy in these contexts might target various complementary aspects of the ecosystem (e.g., actions that enhance the interaction between economic agents and institutions) (Lafuente et al., 2020; Radosevic and Yoruk, 2013).

When the analysis focuses on outcomes more directly connected to country-level entrepreneurship, the key findings reveal that quality changes in the ecosystem based on the BOD-GEI prescription are positively correlated to variations in venture capital investments in early-stage and established businesses. Despite our analysis is constrained by data limitations,[8] this result is in line with prior work emphasizing that venture capital patterns are shaped by the characteristics of the local entrepreneurial ecosystem (e.g., Drover et al., 2017; Munari and Toschi, 2015).

In light of the study results, which correlate the growth in venture capital investments to improvements in the 'networks' and 'technology absorption' pillars, the development of regulatory frameworks (e.g., risk capital regulation) might be insufficient to consolidate venture capital markets. Venture capital boosts entrepreneurial initiatives by injecting capital and other intangibles (e.g., managerial expertise or access to networks) to new and established businesses. A solid entrepreneurial ecosystem may well be a prerequisite for the consolidation of venture capital markets; therefore, entrepreneurship policy aimed at enhancing these markets should include actions supporting different aspects of the entrepreneurial ecosystem (Bruton et al., 2005; Drover et al., 2017; Li and Zahra, 2012). Example of such policies may include, among others, the development of formal business networks, informal institutions that increase market's legitimacy and social connections between investors and entrepreneurs, as well as the promotion of knowledge transfer that facilitates the channeling of technology to entrepreneurs and established businesses.

Credit author statement

Esteban Lafuente, Zoltan Acs and László Szerb contributed to writing and revising all the sections of the manuscript. The authors approve the content of this manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[8] For example, we cannot distinguish whether venture capital activity is supported by public administrations or is exclusively a result of private investors' incentives. Also, because of the difficulties to breakdown investors' target markets we work with a narrow definition of venture capital that includes investments in both early-stage ventures and established businesses. Finally, the data does not allow to identify whether venture capital activities take place in more traditional capital markets or in digital platforms (crowdfunding).

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2021.104379.

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