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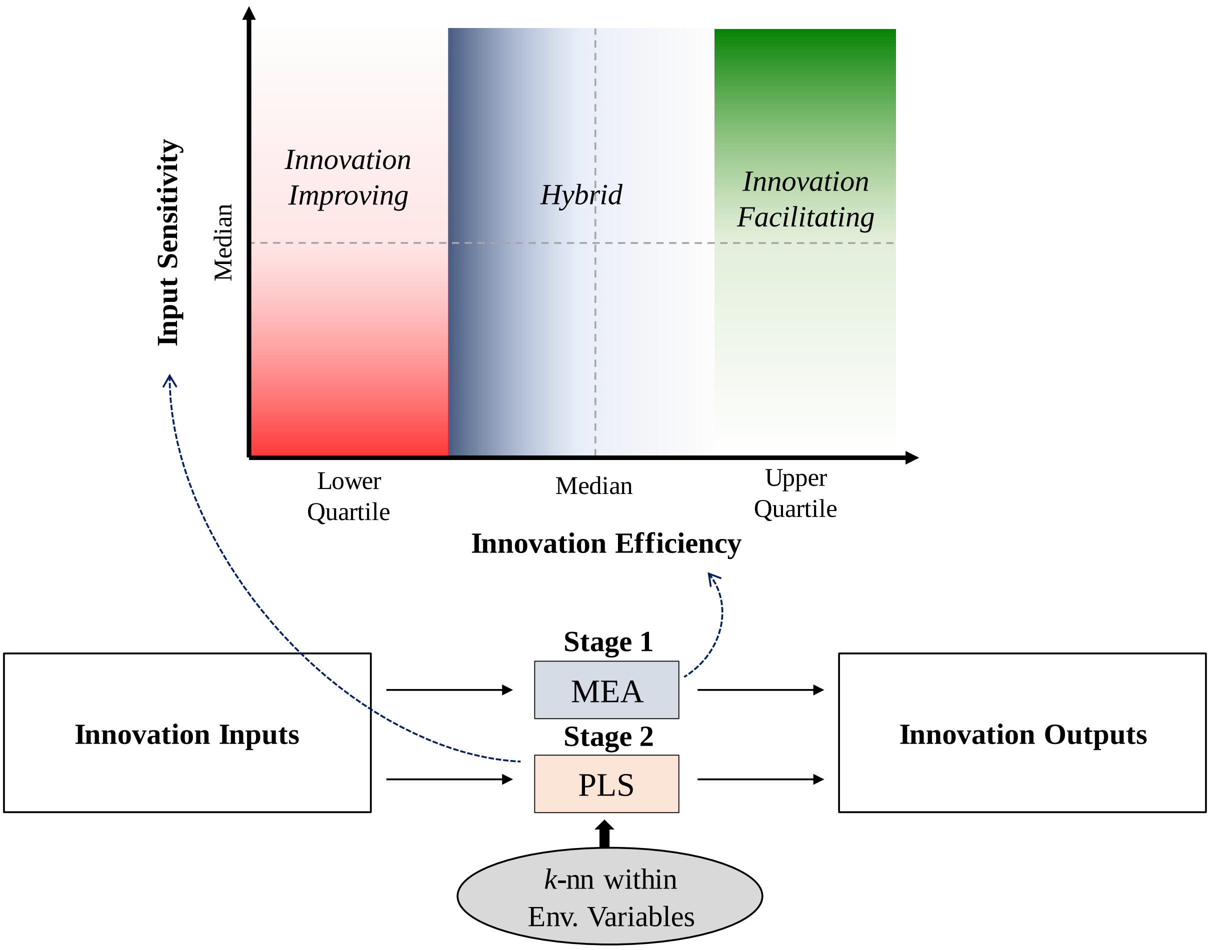
Highlights

- Two-step model introduced to identify tailored innovation policies for each country
- Nearest neighbors within a user-set environment are used to condition regressions
- We find asymmetric patterns in innovation efficiency across countries
- Responsiveness to innovation inputs is not associated with income or geography
- Three policy directions are proposed within the efficiency-responsiveness space

Graphical Abstract



A data envelopment analysis and local partial least squares approach for identifying the optimal innovation policy direction

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Abstract

The paper proposes a novel two-step approach that evaluates countries' innovation efficiency and their responsiveness to expansions in their innovation inputs, while addressing shortcomings associated with composite indicators. Based on our evaluations, we propose innovation policies tailored to take into account the diverse economic environments of the many countries in our study. Applying multidirectional efficiency analysis on data from the Global Innovation Index, we obtain separate efficiency scores for each innovation input and output. We then estimate different sensitivities for each country, by applying partial least squares on explanatory and response matrices which are determined by the nearest neighbors of the country under consideration. The findings reveal substantial asymmetries with respect to innovation efficiencies and sensitivities, which is indicative of the diversity of national innovation systems. Considering these two dimensions in combination, we outline three policy directions that can be followed, offering a platform for better-informed decision-making.

Keywords: data envelopment analysis; multi-directional efficiency analysis; nearest neighbors; innovation policy

JEL classification: C44, O30, O38, O57

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1. Introduction

Innovation is successful when new knowledge is developed, adopted and disseminated, both within a country, as well as across borders (Cassiman & Veugelers, 2002). An important dimension that is often overlooked is innovation efficiency, which has received more attention since the financial crisis (Cruz-Cázares, Bayona-Sáez, & García-Marco, 2013). Niosi (2002) attributes innovation inefficiency to a number of factors, including bounded rationality, transactions costs and lock-in situations. Despite the potential benefits of successful innovation, misallocating resources in search of innovative business practices and processes is detrimental to firms. After the world recession in the late 2000's many firms cut back on their R&D investments since they viewed these as discretionary expenditures. During this period firms also faced substantial difficulties in obtaining external financing. Innovation was mainly concentrated in established and well-resourced firms. All of these factors have contributed to the declining investments that have been observed in R&D projects (Archibugi, Filippetti, & Frenz, 2013). As the particular circumstances and the institutional constraints to investments in innovation are not well-understood, identifying how innovation resources can be optimally allocated is an important policy concern for governments and an important competitive insight for key industrial sectors and for firms therein. Public financing can help firms to sustain innovation investments, as Paunov (2012) shows for countries in Latin America and Atanassov (2016) for a large panel of US companies, while it also has an active role in supporting risky innovations (Mazzucato & Semieniuk, 2017). This creates an added imperative for the efficient use of scarce public resources, which are often misallocated when outcomes are erroneously viewed as easily observable or when political expediency obscures the difficulties in obtaining outcomes that are not easily measured. Despite the fact that various approaches for measuring innovation efficiency have been proposed, two important elements are often missing, at least in combination: (1) accounting for the diversity of national innovation systems (NIS), which makes benchmarking or ranking winners and losers problematic; (2) evaluating the responsiveness of innovation outputs to innovation-related investments. This paper considers both of these important elements.

Policymakers often use composite indicators such as the Global Innovation Index, the European Innovation Scoreboard, the Innovation Capability Index, or the Global Competitiveness Index, to measure countries' innovation performance. A selection of variables that reflect various aspects of innovation are commonly aggregated into a single score. The most comprehensive composite innovation index in terms of country coverage and the spectrum of indicators used is the Global Innovation Index (GII), where the analysis is complemented with the evaluation of countries' innovation efficiency ratio (IER). Measuring innovation efficiency through composite indicators comes with limitations arising from the use of simple arithmetic or geometric averages (Fusco, 2015). Most importantly, the diversity of NIS is not adequately captured, as we explain in detail in later sections. Data envelopment analysis (DEA) has been used to address this issue in applications that measure the innovation efficiency of countries or regions (Carayannis, Grigoroudis, & Goletsis, 2016; Han, Asmild,

& Kunc, 2016), or in evaluating the efficiency of innovation systems (Guan & Chen, 2012). It has also been used to calculate weights in the construction of composite indicators (see Cherchye, Moesen, & Puyenbroeck, 2004; Despotis, 2005; Kao et al., 2008). In fact, the GII report includes a robustness check that compares the IER-based rankings with country rankings based on the constant returns to scale DEA model of Charnes, Cooper, & Rhodes (1978).[1] However, even if weights are determined through optimizing models, such as DEA, instead of using simple arithmetic or geometric averages, such models often do not address the added problem of compensability. As an example, the DEA model used in the robustness exercise of the GII is not free from this issue.

Our paper proposes a novel two-step framework to tailor innovation policies suitable for each country while providing modifications that address the problems we have pointed out above. The analysis is based on the relationship between a country's sensitivity to innovation-related investments and the associated resource misallocation. To account for the latter, we obtain innovation efficiency scores using the multi-directional efficiency analysis (MEA) approach (Asmild, Hougaard, Kronborg, & Kvist, 2003; Bogetoft & Hougaard, 1999), explained in detail in section 3. Since MEA is a directional model of efficiency and given the fact that it imposes a different directional vector for each country, it is better suited to deal with the aforementioned compensability issue (Fusco, 2015).[2] Moreover, the fact that individual efficiency scores are calculated for each innovation input and output variable, makes MEA more effective in capturing the diversity of national innovation systems (NIS).

In order to evaluate the responsiveness (sensitivity) of innovation outputs to changes in innovation inputs for each country, we propose an iterative multivariate regression approach where the sample of countries varies according to a clustering algorithm, outlined in detail in section 3. In particular, we apply partial least squares regression (PLS) (Höskuldsson, 1988; Wold, Ruhe, Wold, & Dunn, III, 1984) on the innovation input (explanatory) and output-related (response) variables, since PLS regression is designed for multivariate systems.[3] PLS is one of many dimension reduction methods used in data

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[1] The DEA problem in this comparison is modified somewhat to ensure that each input has neither a non-negligible, nor a dominant weight, the former weight restriction imposed in order to "…*preclude the possibility of a country achieving a perfect score by assigning a zero weight to weak pillars*." For more on this see GII (2016, p.72).

[2] The issue of compensability is of concern in applications where optimizing algorithms are used to calculate alternative scores for composite indicators, compared to the ones resulting from simple averaging and linear aggregation. The problem of perfect compensability also extends to the benefit of the doubt (BoD) approach, which calculates weights that reflect trade-offs between variables. Including weight restrictions (as in the robustness exercise in the GII) deals with the issue partially. However, it does not completely offset it as the resulting weights still represent common trade-offs for all units in the restricted space. Fusco (2015) introduces a directional BoD model which includes a "directional penalty", which simply replaces the radial DEA efficiency measure with a directional one. MEA is one of the possible approaches for choosing the directional vector.

[3] It is important to note that PLS regression, used in this paper, and PLS path modelling, are two distinct branches that share similar origins but are associated with substantially different algorithms. They should not be confused. In this paper, we use the abbreviation PLS to refer to the former.

mining and is much like principle components analysis (PCA) in that it can deal with systems that may suffer from collinearity. PLS has the additional benefit that it can account for latent factors (Wold, Sjöström, & Eriksson, 2001), such as the ones underpinning the transformation of innovation inputs into outputs. To obtain country-specific sensitivities, we run a local PLS regression for each country in the sample, while varying the nearest neighbors (peer countries) of the reference country. Given that we define the neighborhood in terms of three economic variables (R&D as a percentage of GDP, FDI inflows as a percentage of GDP and trade openness) our contribution translates to incorporating the notion of economic proximity in innovation policy evaluation, which extends beyond geographical or income boundaries. Finally, using the resulting relationships between the sensitivities and the innovation efficiency scores, our analysis can point out the optimal policy direction that a country should follow: *innovation facilitating*, *innovation-improving* or *hybrid*.

To anticipate empirical results discussed in section 4, we find substantial asymmetries in innovation efficiencies and estimated sensitivities. For example, high-income countries in Europe are more innovation-efficient on average than their counterparts elsewhere, while low-income countries seem to prioritize knowledge and technology outputs over creative ones. On the contrary, the diversity in the estimated sensitivities cannot be associated with income or geography. We find, though, that countries are on average more responsive to investments in human capital and research, whereas factors related to knowledge linkages and transfers in the business community are associated with the lowest sensitivities. When jointly considering innovation input efficiencies and output sensitivities, we demonstrate that a new dimension is added to the empirical analysis of innovation, and we suggest innovation policy directions for each country. Our results indicate that the direction that a country should follow can be different with respect to each (input) efficiency - (output) sensitivity combination considered. Therefore, a more tailored approach is necessary in order to identify the most promising areas for innovation investments and avoid misallocating resources.

The remainder of the paper is organized as follows. Section 2 outlines how the Global Innovation Index is constructed and discusses in more detail the issues with its use that we have alluded to above. Section 3 outlines the proposed two-step framework we employ in our analysis and discusses other methodological and technical aspects. Section 4 describes the data, presents the empirical results, and discusses implications for policy design. Section 5 concludes. More detailed results of our analyses are provided in the accompanying Supplement.

2. Composite indicators of innovation-related activities

The 2016 Global Innovation Index (GII) assesses the innovation performance of 128 countries through the aggregation of 82 indicators. The aim of the GII is to facilitate policy-making by identifying a country's relative ranking vis-à-vis other countries in terms of these different indicators. The indicators are aggregated into groupings that are referred to as 'pillars'. The first level of aggregation combines the 82 indicators into sub-pillars and these are subsequently aggregated into the five input pillars

(*Institutions, Human Capital & Research, Infrastructure, Market Sophistication, Business Sophistication*) and the two output pillars (*Knowledge & Technology* and, *Creative Outputs*) that we utilize in our analyses. The input pillars are averaged to derive the Innovation Input Sub-Index, while averaging the output pillars generates the Innovation Output Sub-Index. Finally, the GII score is computed as the simple average of the Innovation Input and Output Sub-Indices, while the Innovation Efficiency Ratio (IER) is determined by the ratio of the Innovation Output Sub-Index to the Innovation Input Sub-Index. Country rankings based on the GII score differ relative to those based on the IER, as the GII focuses on the magnitude of innovation activities while the IER evaluates the extent to which the available innovation resources have been productively utilized.

A common issue with composite indicators that follows from this process of linear aggregation is that the resulting weights attached to the indicators are compensatory (scaling coefficients), in that low values in one indicator would be perfectly offset by high values in another, without affecting the associated scores. In our context this would suggest, for example, that an increase in *Creative Outputs* could compensate for a decrease in the *Knowledge & Technology* output, leaving the associated metrics (the Innovation Output Sub-Index, and therefore the GII and the IER scores) unaffected. This is arguably somewhat counterintuitive. The problem of compensability also extends to multicriteria models, if not treated appropriately, as well as the standard DEA-based benefit of the doubt (BoD) approach (Cherchye et al., 2004), which is used in the robustness exercise of the GII. In the latter case, directional distance functions have been used to address compensability (Fusco, 2015; Vidoli, Fusco, & Mazziotta, 2015).

A related issue, shared by simple averaging and conventional BoD and DEA models, is that they do not fully account for the diversity of national innovation systems (NIS). This is clear for the case of simple averaging since weights are given *a priori*. Regarding DEA-based methods, despite the fact that they can signal the importance of particular variables by assessment of their relative weights generated from an optimization problem, their effectiveness is reduced when radial measures of efficiency are used. This is because innovation inefficiencies determined by conventional BoD and DEA models would indicate equiproportional improvements in inputs and/or outputs, as the calculated weights are consistent with this interpretation. However, the well-documented diversity of NIS is multifaceted and can be influenced by various factors such as capabilities, resources, the environment or the pace of technological change (Grupp & Schubert, 2010; Watkins, Papaioannou, Mugwagwa, & Kale, 2015). Therefore, there are asymmetries in countries' preferences and priorities with respect to innovation that need to be taken into account.

The sources of these asymmetries can be evaluated by examining a country's potential improvements in each dimension considered. We carry out such an analysis using the multi-directional efficiency analysis (MEA) model, which estimates directional vectors of potential efficiency improvements with respect to each innovation input and output. MEA, being a directional measure of efficiency, is well-suited for dealing with the compensability issue, while it is more effective compared to other approaches in capturing the diversity of NIS since it allows each country to optimize in each input-output dimension separately.

Another consideration relates to how to plausibly evaluate a country's responsiveness to innovation-related investments, also taking into account the dynamism of the environment. Some countries may be exposed to a substantially less conducive environment to innovation and their ability to innovate or the feasibility of achieving certain targets of innovation activity may be overstated, if the influences of the environment are not taken into account. For example, the GII report classifies countries as 'underperformers', 'achievers' and 'leaders' (Figure 4, GII, 2016, p. 32) without considering the proximity of their economic environments, which is influential for the development and adoption of innovations. In this paper, we emphasize on countries' attitude towards internationalization and R&D investments, which have received extensive support in the literature for promoting innovation.[4] In particular, we account for the role of the environment when evaluating the sensitivity of innovation outputs to innovation inputs, under three dimensions: foreign direct investments (FDI), research and development (R&D) expenditure and trade openness.[5]

The first dimension considered, FDI, contributes to innovation in a number of ways. First, FDI act as channels for knowledge and technology transfers (Blomström & Sjöholm, 1999; Sinani & Meyer, 2004), while they can have a wider economic impact due to intra-industry productivity spillovers (Javorcik, 2004). Second, FDI promote innovation through capital transfers and by alleviating the financial constraints that firms may face in the host country (Chen, Hua, & Boateng, 2017; Kerr & Nanda, 2015). Moreover, skilled labor mobility is increased through FDI, thus contributing to innovation by increasing human capital stock and enhancing technological capabilities (Bosetti, Cattaneo, & Verdolini, 2015; Fassio, Montobbio, & Venturini, 2019). However, a key factor for the successful transfer of know-how and the adoption of new technologies through FDI is absorptive capacity (Ferreras-Méndez, Newell, Fernández-Mesa, & Alegre, 2015; Xie, Zou, & Qi, 2018); the ability to apply knowledge acquired externally (Cohen & Levinthal, 1990; Zahra & George, 2002). Given that absorptive capacity varies widely around the world (Archibugi & Coco, 2005), it is important for its role to be accounted for.

Among the factors used in the literature to proxy for absorptive capacity (Griffith, Redding, & Van Reenen, 2003; Sánchez-Sellero, Rosell-Martínez, & García-Vázquez, 2014), we use R&D expenditure which has a dual role in innovation. On the one hand, R&D expenditure is a prerequisite for the

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[4] For a comprehensive review on the nexus between internationalization, innovation and productivity, please see Cassiman & Golovko (2018).

[5] We decided to include only supply-based measures given that we are assessing a transformation relationship of innovation inputs to outputs and given the fact that policymakers can exert some control over them. Demand-based factors can be directly or indirectly related to outcomes of the innovation process and we wish to avoid possible endogeneity issues. We should also note that, depending on the policy objective, it would be possible to consider an alternative set of environmental variables. For further details along with a robustness exercise please see Footnote 12.

development of new technologies, while it increases firm productivity (Kancs & Siliverstovs, 2016). On the other hand, internal R&D enhances the technological capabilities of firms through better assimilation and exploitation of external information (Aghion & Jaravel, 2015; Cohen & Levinthal, 1989). Empirical studies have also confirmed that, R&D intensity, the ratio of R&D expenditure to total output, has a significant role in productivity growth and that it is a good proxy of absorptive capacity (Aldieri, Sena, & Vinci, 2018; Eaton, Gutierrez, & Kortum, 1998; Griffith, Redding, & Reenen, 2004).

The third dimension is trade openness, which is commonly used as a measure of economic distance (Glass, Kenjegalieva, & Sickles, 2016). Trade, not only does it promote R&D spillovers (Fracasso & Vittucci Marzetti, 2015), but it also expands the potential market size and provides incentives to innovate due to product market integration and intensified competition (Grossman & Helpman, 1990, 1994). A reduction in trade barriers, therefore, promotes process innovations as firms need to improve their productive and cost efficiency in order to survive global competition and bear the costs of exporting (Atkeson & Burstein, 2010; Desmet & Parente, 2010; Long, Raff, & Stähler, 2011). The empirical evidence also shows that such a reduction in trade barriers reallocates skilled labor towards technologically advanced firms (Bloom, Draca, & Van Reenen, 2016).

Taking into consideration the above, we propose a novel approach that first identifies each country's nearest neighbors within the aforementioned dimensions, and then evaluates each country's responsiveness to innovation inputs. The combination of innovation efficiency and country-specific sensitivities is then used to propose innovation policy directions for each country. The details of our framework are discussed in the next section.

3. Methodology

We now explain how we address the aforementioned issues and how we account for the diversity of national innovation systems (NIS) and the role of the environment using a two-step framework. The first step uses the multi-directional efficiency analysis (MEA) approach to obtain non-radial efficiency scores with respect to each input-output dimension. In the second step, we introduce a new approach to estimate country-specific sensitivities of innovation outputs to changes in innovation inputs.

3.1 Multi-directional efficiency analysis

In the first step of our framework, we measure innovation efficiency using the multi-directional efficiency analysis (MEA) model (Asmild et al., 2003; Bogetoft & Hougaard, 1999), which builds on the framework of data envelopment analysis (DEA). The choice of a non-parametric technique also finds support in Niosi (2002), who formalized the concept of X-inefficiency for NIS. MEA is a directional efficiency measurement approach that assesses countries' potential improvements in each dimension and, therefore, it is possible to obtain individual efficiency scores for each innovation input and output. The resulting efficiency scores can be used to examine for asymmetric patterns in the use of innovation resources across countries. Such asymmetries are indicative of the diversity of NIS and of the differences in national priorities. Given the above and the fact that MEA can deal with the issue of compensability, as previously explained, it is a suitable model to be used in this context.

Consider a set of n decision making units (DMUs) or countries where $i = 1, \dots n,$ that use p inputs $(j = 1, \dots p)$ to produce q $(r = 1, \dots q)$ outputs. Let DMU k have a production plan $(\boldsymbol{x}_k, \boldsymbol{y}_k)$, where $\boldsymbol{x}_k = (x_{k,1}, \dots x_{k,p})$ and $\boldsymbol{y}_k = (y_{k,1}, \dots y_{k,q})$. In the first step, we calculate potential improvements in inputs and outputs for each DMU. We start by defining the ideal reference point for the k^{th} DMU, denoted as $(\boldsymbol{x}_k^*, \boldsymbol{y}_k^*) = (x_{k,1}^*, \dots x_{k,p}^*, y_{k,1}^*, \dots y_{k,q}^*)$. To determine the coordinates of the ideal reference point, we use as many linear programs as dimensions. Consistent with the literature on composite indicators (Guan & Chen, 2012; Kao et al., 2008), we assume constant returns to scale (CRS). Moreover, we use a non-oriented model given that the innovation outputs are, in principle, controllable, while innovation inputs require significant investments and effort to be developed and sustained to the desirable level.[6] For the j^{th} input of DMU k, the ideal reference point is obtained using the following linear program:

$$
\begin{aligned}
&\min_{\lambda, x_{k,j}^*} \{x_{k,j}^*\} \quad \text{s.t.} \\
&\sum_{i=1}^{n} \lambda_i x_{i,j} \leq x_{k,j}^* \\
&\sum_{i=1}^{n} \lambda_i x_{i,-j} \leq x_{k,-j} \quad \text{for} \quad -j = 1, \dots j-1, j+1, \dots p \\
&\sum_{i=1}^{n} \lambda_i y_{i,r} \geq y_{k,r} \quad \text{for} \quad r = 1, \dots q \\
&\lambda_i \geq 0
\end{aligned}
\tag{1}
$$

For the r^{th} output of DMU k, we have:

$$
\begin{aligned}
&\max_{\lambda, y_{k,j}^*} \{y_{k,r}^*\} \quad \text{s.t.} \\
&\sum_{i=1}^{n} \lambda_i x_{i,j} \leq x_{k,j} \quad \text{for} \quad j = 1, \dots p \\
&\sum_{i=1}^{n} \lambda_i y_{i,r} \geq y_{k,r}^*
\end{aligned}
\tag{2}
$$

[6] To examine the sensitivity of MEA scores to sampling variations we implement the *m/n* bootstrap (Simar, Vanhems, & Wilson, 2012). Compared to the case of directional distance functions, the computational costs for implementing the *m/n* bootstrap on MEA are $2 \cdot (p + q)$ higher. We therefore search for the optimal block size (Politis, Romano, & Wolf, 2001) only within a limited range of blocks, deduced from the simulations of Kneip, Simar, & Wilson (2008). We find that the resulting confidence intervals are reasonably narrow, while the rank correlations between the MEA efficiency scores and the bias-corrected ones are very high (above 0.98). The results of this exercise can be found in the accompanying Supplement.

$$\sum_{i=1}^{n} \lambda_i y_{i,-r} \geq y_{k,-r} \quad \text{for} \quad -r = 1, \dots r-1, r+1, \dots m$$
$$\lambda_i \geq 0$$

The linear programs above identify the maximum potential improvements with respect to each input and output, consecutively defining each coordinate of the ideal reference point of DMU k. This point may lie outside the feasible set, but it is only used to indicate the direction of improvement for DMU k in each dimension. If $(\boldsymbol{x}_k^*, \boldsymbol{y}_k^*) = \left(x_{k,1}^*, \dots x_{k,p}^*, y_{k,1}^*, \dots y_{k,q}^*\right) = (\boldsymbol{x}_k, \boldsymbol{y}_k)$, DMU k utilizes its inputs efficiently, while it produces the efficient level of outputs and, therefore, there is no scope for further improvement. However, if $(\boldsymbol{x}_k^*, \boldsymbol{y}_k^*) \neq (\boldsymbol{x}_k, \boldsymbol{y}_k)$, the DMU k should improve in the direction of the ideal reference point $(\boldsymbol{x}_k^*, \boldsymbol{y}_k^*)$.

Denote now the distance of the j^{th} input and r^{th} output of the ideal reference point from the observed ones as $d_{k,j} = x_{k,j} - x_{k,j}^*$ and $\delta_{k,j} = y_{k,r}^* - y_{k,r}$, respectively. In the second step, the proportion β of the distances ($d_{k,j}$ and $\delta_{k,j}$) from the ideal reference point are identified. If $\beta = 0$, DMU k is by definition efficient, whereas if $\beta > 0$, there are potential improvements in all directions. We estimate β with the following linear program:

$$\max_{\lambda,\beta}(\beta) \quad \text{s.t.}$$
$$\sum_{i=1}^{n} \lambda_i x_{i,j} \leq x_{k,j} - \beta d_{k,j} \qquad \text{for} \quad j = 1, \dots p \tag{3}$$
$$\sum_{i=1}^{n} \lambda_i y_{i,r} \geq y_{k,r} + \beta \delta_{k,r} \qquad \text{for} \quad r = 1, \dots q$$
$$\lambda_i \geq 0$$

The target level of inputs and outputs for DMU k, denoted as $\boldsymbol{x}_k^T = \left(x_{k,1}^T, \dots x_{k,p}^T\right)$ and $\boldsymbol{y}_k^T = \left(y_{k,1}^T, \dots t_{k,p}^T\right)$ respectively, are computed as:

$$x_{k,j}^T = x_{k,j} - \beta_k d_{k,j}$$
$$y_{k,r}^T = y_{k,r} + \beta_k \delta_{k,r} \tag{4}$$

Following Asmild and Matthews (2012), we determine the relative efficiency scores for each input as the ratio of the target inputs over the actual ones, denoted as $\theta_{k,j} = \left(x_{k,j}^T / x_{k,j}\right)$ for each DMU. Similarly, the relative efficiency scores for each output are determined as $\theta_{k,r} = \left(y_{k,r} / y_{k,r}^T\right)$. Instead of interpreting inefficiencies as required input contractions or output expansions, we use them to identify resource misallocations in the innovation process. Taking also into account that multiple indicators are included in the construction of the input and output pillars, which are obtained from data that span a decade, if not more (GII, 2016, 393), the calculated inefficiencies are likely to persist. Therefore, inefficiencies could be also thought to reflect as potential resource misallocations. Finally, we derive an aggregate measure of MEA efficiency using the following aggregation (Asmild and Matthews, 2012):

$$\rho_k = \left(1 - \frac{1}{p}\sum_{j=1}^{p}\frac{d_{k,j}\beta_k}{x_{k,j}}\right) \Bigg/ \left(1 + \frac{1}{q}\sum_{r=1}^{q}\frac{\delta_{k,r}\beta_k}{y_{k,r}}\right) \quad (5)$$

3.2 Sensitivity conditional on economic proximity

The second step of our framework estimates country-specific sensitivities of innovation outputs to changes in innovation inputs. This is operationalized by implementing a multivariate regression framework (local PLS regression) where the logs of innovation outputs are regressed on the logs of innovation inputs, while conditioning on each country's nearest neighbors (or peer countries).[7] Conceptually, our approach is closer to the conditional efficiency literature (Bădin, Daraio, & Simar, 2010; Daraio & Simar, 2014), but with the difference that they examine the influence of environmental factors on efficiency, instead. Methodologically, the closest approach to ours is that of Guan & Chen (2012), but with the fundamental difference that they apply a PLS regression on efficiency scores to address a different research question. Therefore, our paper differs both in terms of research objectives and the approach it implements to address them.

PLS is a multivariate regression approach that can be used to model the relationship between a response matrix and an explanatory matrix. It belongs to the same family of models as principal components regression, canonical correlation, and ridge regression, and it is more suitable when the column-wise (variables) correlations are high or when one does not want to impose assumptions on the distribution of the error term. We choose to use PLS over alternative suitable candidates, as it can estimate different sensitivities for each input-output combination and, therefore, allows us to evaluate whether investments in certain innovation inputs would find greater response in *Knowledge & Technology* outputs or *Creative Outputs*.[8]

Following Wold et al. (2001) and in line with the notation in subsection 3.1, denote with $\boldsymbol{X}$ the $n \times p$ explanatory matrix containing the logs of innovation inputs and with $\boldsymbol{Y}$ the $n \times q$ response matrix of the logs of innovation outputs. The $\boldsymbol{X}$ and $\boldsymbol{Y}$ matrices are decomposed into orthogonal components as:

$$\boldsymbol{X} = \boldsymbol{TP}' + \boldsymbol{E} \quad \text{and} \quad \boldsymbol{Y} = \boldsymbol{UC}' + \boldsymbol{G} \quad (6)$$

where $\boldsymbol{T}$ and $\boldsymbol{U}$ are score matrices, $\boldsymbol{P}$ and $\boldsymbol{U}$ are factor loading matrices, while $\boldsymbol{E}$ and $\boldsymbol{G}$ are residual matrices, reflecting unexplained variability. PLS regression establishes a linear model that maximizes the covariance between the components of $\boldsymbol{Y}$ and $\boldsymbol{X}$:

$$\boldsymbol{Y} = \boldsymbol{TC}' + \boldsymbol{F} = \boldsymbol{XB} + \boldsymbol{F} \quad (7)$$

---

[7] It is important to note that the estimated sensitivities are the expected responses of outputs to inputs within each country's set of nearest neighbors. Therefore, these partial derivates cannot be used for the characterization of returns to scale and they should not be confused with scale elasticities.

[8] Multivariate least squares would only generate as many estimates as explanatory variables. Similarly, when the explanatory variables are common for all response variables, as in our case, the estimated coefficients from a seemingly unrelated regressions system are as many as the (common) explanatory variables.

where $\boldsymbol{F}$ is a matrix of Y-residuals between observed and estimated responses and $\boldsymbol{B}$ is the matrix of PLS regression coefficients. Let β_{ij} be the estimated PLS coefficient of the correspondence between the i^{th} innovation input and the j^{th} innovation output. Since $\boldsymbol{X}$ and $\boldsymbol{Y}$ are expressed in logs, the estimated coefficients reflect the sensitivity (responsiveness) of innovation outputs to changes in innovation inputs. Hence, the greater (smaller) the value of β_{ij}, the greater (smaller) the responsiveness of innovation output j to investments in innovation input i.

In our paper, we adjust this framework to account for the influences of the environment, defined through a multidimensional space of user-set variables (here economic proximity). To do so, we first identify the nearest neighbors (peers) of each country, defined as those γ countries that exhibit the smallest squared Euclidian distance from the reference country, in terms of their environmental variables. To determine the optimal number of nearest neighbors (denoted as γ^*), we try different values for γ, ranging from $p+1$ to $n-p-1$. Each time, we construct for a reference country k, a $\gamma \times p$ explanatory matrix X_γ^k and a $\gamma \times q$ response matrix Y_γ^k, which contain the innovation inputs and outputs of the nearest neighbors of the reference country. We apply the PLS regression of Y_γ^k on X_γ^k to obtain a $\gamma \times q$ matrix of residuals and calculate their element-wise sum of squares $SSE_\gamma^k = \sum_{i=1}^{n}\sum_{j=1}^{q} e_{ij}^2$. We repeat this process for every country and calculate the aggregate sum of squares as $SSE_\gamma = \sum_{i=1}^{n} SSE_\gamma^i$. The optimal number of nearest neighbors γ^* is the one that returns the minimum SSE_γ. Our approach generates sensitivity estimates for each country and therefore the total number of estimated coefficients is $n \times p$ for each output, which are all determined from the n local PLS regressions corresponding to the γ^* number of neighbors.

As a robustness check we use a multi-layer perceptron (MLP), which is treated as a performance benchmark to evaluate whether PLS can approximate the underlying data model adequately. MLP is a feed-forward neural network which, due to its non-linear nature, can fit the data closely and is therefore expected to produce low SSE.[9] We find that the SSE of the PLS regression when applied on the full data set is 9.27, which is close to minimum one for MLP of 8.07, obtained through an iterative process. Given also the straightforward interpretation of the regression estimates obtained from local PLS regressions and the ability to extract country-wise sensitivities, we conclude that PLS is suitable for addressing the research objectives of this study.

4. Empirical analysis and policy implications

This section applies the two-step framework on the GII data and presents and discusses the empirical findings, along with the policy implications arising. We start by providing an overview of the data along with some first insights. We then analyze the MEA innovation efficiency scores for each region and

[9] We thank an anonymous referee for this suggestion. Further details of this exercise are provided in the accompanying Supplement.

income group. Next, we discuss the results arising from the PLS regression and propose policy directions that consider countries' MEA innovation efficiencies and sensitivities (PLS coefficients), simultaneously.

4.1 Data

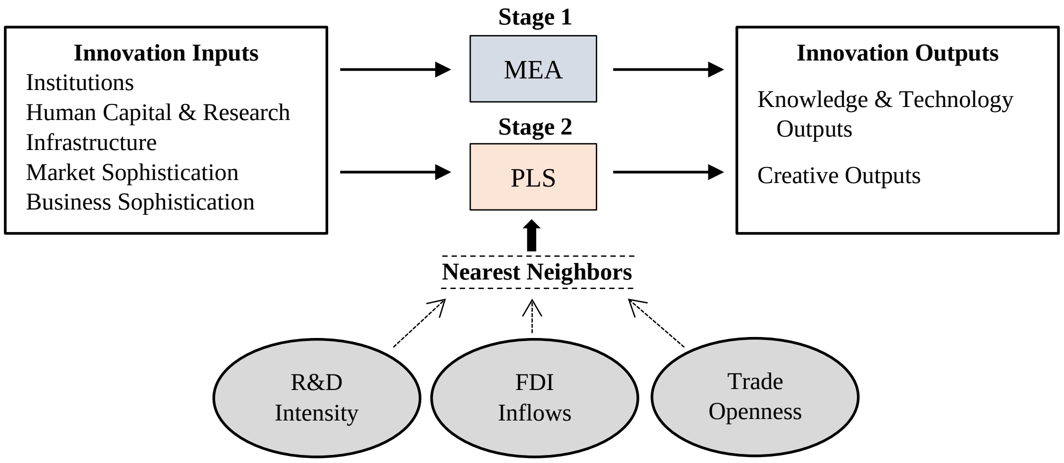
We obtain input-output data for 128 countries from the GII (2016) report and we use its five innovation input pillars as the input variables and its two innovation output pillars as the output variables to calculate MEA scores in the first step of our approach. The indicators used to build the GII framework, and therefore the data used in this study, have undergone a four-step process to ensure coherence and that different aspects of innovation are adequately represented (GII, 2016, p. 61).[10] Therefore, the input and output pillars that we use for our efficiency computations reflect different aggregated dimensions of innovation. Our aim is to show how the empirical findings in the GII report can be more informative by incorporating innovation efficiency and output responsiveness in the analysis. We show later in the paper that these two concepts are independent with each other and with the GII scores, suggesting that further disaggregation would not be necessary to achieve our goals.

The logarithms of the innovation inputs and outputs are then used in our PLS framework. The nearest neighbors (peers) are determined for each country through three economic variables (economic proximity). The first variable we use is R&D expenditure (% GDP), in order to account for the intensity of R&D investments in a country. The second variable is FDI net inflows (% GDP), emphasizing the benefits to the host country from inward investments. Finally, to account for trade, we use trade openness which is defined as the ratio of the sum of a country's imports and exports to its GDP. The data for the economic variables are obtained from the World Bank and we use the latest available observations. Our methodological framework is flexible for policy experimentation, in that a different set of qualitative or quantitative variables or dimensions of proximity can be accommodated to suit policy objectives.[11] The data flow within our two-stage framework is presented in Figure 1 below.

[10] In the first step, the conceptual consistency is examined, where candidate variables/indicators are selected and innovation pillars are defined, based on the relevant literature. The second step involves checking whether the data, derived from a wide range of sources, conforms to requirements for availability and coverage. In this step, among other data treatments, the raw data from the variables are normalized to produce the 82 indicators that appear in the GII (2016) report, and in order to facilitate aggregation. The next step involves determining the weights applied to each indicator, as well as grouping indicators into sub-pillars and subsequently into pillars and sub-indices. Moreover, the statistical coherence of the GII is assessed through principal component and reliability item analysis. In the last step, the overall results are reviewed qualitatively to assess their consistency with other evidence and research, concluding, though, that the GII framework is open for future development (GII, 2016, p. 64).

[11] Using an alternative set of environmental variables would only affect the estimated sensitivities, leaving the policies we propose later in the paper unchanged. We demonstrate this in the accompanying Supplement by including an institutional factor, the level intellectual property rights protection, in the set of environmental variables, given its cited importance for

Figure 1. Two-stage framework and data flow illustration



Notes: The figure provides a schematic representation of the data flow within our two-stage framework

Table 1 provides a summary of the variables used in our analysis. There is substantial variability in the inputs and outputs, which largely relates to geography given the asymmetries observed in the regional averages. The *Human Capital & Research* pillar appears with a relatively low value compared to the other input pillars, mostly in low-income regions, such as Sub-Saharan Africa. Moreover, only few countries have environments conducive to innovation, reflected in the positively skewed and leptokurtic distributions of the three variables that we use to define economic proximity. The substantial variability that countries exhibit with respect to these three variables is also indicative of the heterogeneity of their economic environments, further justifying the use of a clustering algorithm. We also find high correlations between innovation inputs and outputs which may introduce an element of double counting under equal weighting, further supporting the use of optimization-based approaches such as MEA. The high correlations also further justify the use of regression approaches such as PLS, which can deal with multicollinearity. Finally, given that R&D (% GDP) and FDI inflows (% GDP) are indicators within the *Human Capital & Research* and *Business Sophistication* pillars, respectively,[12] we test for endogeneity in these dimensions using the DWH (Durbin–Wu–Hausman) augmented regression test. The case of endogeneity is rejected for both environmental variables and with respect to both outputs.

innovation and links with R&D intensity and FDI (Grossman & Lai, 2004; Helpman, 1993; Lerner, 2009; Maskus, Milani, & Neumann, 2019). We find that the estimated sensitivities are quite robust and that the empirical findings and policy implications of our paper remain unaffected.

[12] In particular, Government Expenditure on R&D (% GDP) is one of the three indicators within one of the three sub-pillars of the *Human Capital & Research* input pillar. Also, FDI net inflows (% GDP) is one of the four indicators within one of the three sub-pillars that comprise the *Business Sophistication* pillar.

Table 1. Summary statistics

	Institutions	Human Capital & Research	Infrastructure	Market Sophistication	Business Sophistication	Knowledge & Technology	Creative Outputs	R&D (% GDP)	FDI inflows (% GDP)	Trade Openness
Descriptive Statistics										
Mean	63.10	33.91	43.36	45.37	33.55	27.59	31.63	0.89	5.36	0.88
Standard deviation	16.35	15.48	13.09	11.63	10.74	12.64	13.99	0.95	10.17	0.63
Skewness	0.09	0.41	-0.02	0.95	0.60	0.85	0.43	1.60	4.21	2.58
Kurtosis	-0.56	-0.65	-0.88	1.05	-0.17	0.35	-0.10	2.08	20.86	9.52
Regional Averages										
Central and Southern Asia	49.46	24.83	35.01	40.62	25.11	19.93	20.73	0.33	3.81	0.55
Europe	76.01	46.74	52.61	49.81	40.39	37.57	43.62	1.44	6.58	1.17
Latin America and the Caribbean	52.93	26.28	40.14	42.29	30.76	18.09	26.10	0.29	4.30	0.54
Northern America	88.70	54.95	62.00	80.10	49.45	48.70	49.35	2.17	2.85	0.47
Northern Africa and Western Asia	60.43	32.01	44.39	42.11	27.12	24.22	28.73	0.60	4.21	0.81
South East Asia and Oceania	69.70	42.99	50.88	56.93	41.50	36.06	37.48	1.33	8.06	1.24
Sub-Saharan Africa	52.42	17.98	28.21	35.92	27.56	18.41	18.98	0.44	4.46	0.69
Correlations										
Institutions	1									
Human Capital & Research	0.755	1								
Infrastructure	0.817	0.851	1							
Market Sophistication	0.695	0.732	0.701	1						
Business Sophistication	0.727	0.762	0.708	0.697	1					
Knowledge & Technology	0.712	0.810	0.740	0.701	0.814	1				
Creative Outputs	0.783	0.765	0.786	0.675	0.739	0.805	1			
R&D (% GDP)	0.635	0.799	0.672	0.650	0.786	0.813	0.676	1		
FDI inflows (% GDP)	0.245	0.148	0.146	0.224	0.328	0.272	0.252	0.003	1	
Trade Openness	0.448	0.299	0.321	0.230	0.418	0.349	0.408	0.124	0.618	1

Notes: The first section of the table present the mean, the standard deviation, skewness and kurtosis for the input and output sub-indices as well as the environmental variables used in this study. The second and third sections report the respective regional averages and correlation coefficients.

4.2 Patterns of innovation efficiency

The empirical findings for the first step of our framework are summarized in Table 2, where innovation efficiency scores are reported per income group and within each region. We use a color map to reflect the quartile of innovation efficiency that each group corresponds to; the darker the color shading, the lower the quartile. Some interesting patterns emerge for the distribution of input and output efficiencies across regions and income groups. Considering the two innovation outputs, we find that, in principle, the respective efficiency scores are high for Europe, Northern America as well as South-Eastern Asia and Oceania (SEAO), which mainly include high-income countries. A balanced score, but of a lower magnitude, is observed for Northern Africa and Western Asia (NAWA), as well as Central and Southern Africa (CSA). On the contrary, Sub-Saharan Africa (SSF), the region that comprises low-income countries (except for Nepal), appears considerably less efficient in *Creative Outputs* compared to *Knowledge & Technology*, while the opposite is true for Latin America and the Caribbean (LCN).[13]

Regarding innovation inputs, we find that most countries exhibit a relatively low efficiency score for the *Human Capital & Research* pillar, which is indicative of the spread of performance in a dimension with cited importance for innovation and economic growth. Although this underperformance appears across income groups and regions, countries in Europe, Northern America and SEAO, which maintain a balanced performance across all dimensions of innovation, seem to be less affected, in principle. Similar underperformance is also observed for the *Market Sophistication* pillar, which captures the credit, investment and competitive conditions in a country, and where high-income countries perform significantly better than others on average.

Comparing countries on the basis of their income and geography reveals considerable variability in results. For example, European high-income groups perform better than their counterparts in other regions, based on the aggregated efficiency score (ρ_k), while the differences are not uniform with respect to each pillar. Similarly, high-income countries in NAWA, which are mostly oil-rich, perform at the bottom quartiles of innovation efficiency. One exception is observed for the innovation-efficient Kuwait, which is dominated by financial services and has a relatively open market. Another notable example is LCN, which includes the most countries performing at the lower quartile, irrespective of income group. The substantial asymmetries in innovation efficiency that we find across income and geographic groups, suggest that different countries have different approaches and priorities when allocating innovation-related resources. On the one hand, inefficiencies may be associated with disproportionately large endowments that certain countries have, and which should be used more productively. On the other hand, high inefficiencies may be indicative of structural weaknesses at the country level, such as transactions costs, complicated bureaucratic procedures, or market frictions, among others, which policy should aim to remove (Niosi, 2002).

[13] The interested reader may refer to Figure S3 in the accompanying Supplement for a visual aggregation of the results per region and for each income group.

Table 2. Innovation efficiency color map

	Institutions	*Human Capital & Research*	*Infrastructure*	*Market Sophistication*	*Business Sophistication*	*Knowledge & Technology*	*Creative*	*Eff(ρ_k)*
Central and Southern Asia								
Low	0.83	0.79	0.87	0.85	0.84	0.85	0.79	0.68
Lower - Middle	0.89	0.84	0.87	0.85	0.90	0.82	0.86	0.73
Upper - Middle	0.85	0.77	0.83	0.85	0.87	0.88	0.83	0.72
Europe								
Lower - Middle	0.98	0.95	0.99	0.97	0.99	0.99	0.98	0.97
Upper - Middle	0.84	0.77	0.86	0.85	0.87	0.86	0.78	0.69
High	0.93	0.88	0.93	0.92	0.94	0.93	0.93	0.86
Latin America and Caribbean								
Lower - Middle	0.85	0.76	0.85	0.77	0.81	0.73	0.85	0.64
Upper - Middle	0.88	0.81	0.86	0.83	0.87	0.80	0.87	0.71
High	0.85	0.79	0.84	0.85	0.88	0.84	0.86	0.72
Northern America								
High	0.92	0.87	0.91	0.86	0.92	0.93	0.90	0.82
Northern Africa and Western Asia								
Lower - Middle	0.90	0.85	0.88	0.88	0.93	0.93	0.86	0.79
Upper - Middle	0.88	0.84	0.88	0.87	0.91	0.90	0.89	0.79
High	0.87	0.82	0.86	0.86	0.90	0.85	0.88	0.76
South East Asia and Oceania								
Lower - Middle	0.94	0.91	0.93	0.89	0.93	0.95	0.94	0.87
Upper - Middle	0.93	0.90	0.93	0.90	0.91	0.93	0.91	0.85
High	0.88	0.80	0.88	0.85	0.89	0.87	0.85	0.74
Sub-Saharan Africa								
Low	0.85	0.82	0.90	0.86	0.85	0.85	0.73	0.65
Lower - Middle	0.94	0.91	0.94	0.91	0.93	0.94	0.93	0.87
Upper - Middle	0.80	0.76	0.85	0.80	0.88	0.78	0.83	0.65

Notes: The table presents the average innovation efficiency scores for each income group within each region, as calculated by MEA. Columns 2 through 6 present the average relative efficiency scores for each input. Columns 7 and 8 present the average relative efficiencies for each innovation output. Column *Eff(ρ_k)* presents the average aggregated MEA efficiency scores, as calculated with the alternative ranking measure ρ_k. A dark grey color is applied to denote the bottom quartile, the patterned grey shading corresponds to the lower-middle quartile, and the patterned light grey shading is used for the upper-middle quartile, while light grey reflects the top quartile. Income groups follow the United Nations 2016 classification. Analytical results for each country can be found in the accompanying Supplement, in Table S1.

4.3 Identifying the optimal policy direction

The findings for the second step of our framework are summarized in Table 3, while results are graphically exhibited in Figures 2 and 3 below, for the *Knowledge & Technology* and *Creative Outputs*, respectively. Table 3 shows the median values of the estimated sensitivities and calculates rank correlations. With regards to the figures, the first column plots the estimated PLS coefficients (sensitivities) against innovation inputs for the innovation output under consideration. The second column plots the estimated sensitivities against the respective MEA efficiency scores. Taking into account the interpretation we attach to pillar inefficiencies, the second column can therefore provide insights on the responsiveness of countries to innovation-related investments, given the potential of resource misallocation. Moreover, to evaluate the role of the 'magnitude' of innovation in our framework, we vary the marker sizes according to countries' GII score.[14] Finally, the coloring in the shaded areas corresponds to different quartiles of efficiency and it is used to aid in the identification of suitable innovation policies for each country.

All sensitivities have positive signs, suggesting that innovation inputs contribute to the expansion of innovation outputs. Looking at the median sensitivities in Table 3, we find that *Human Capital & Research* exhibits the highest values in both innovation outputs (0.30 and 0.35 respectively). A similar picture is observed for the *Infrastructure* pillar, which exhibits the second highest median values (0.20 and 0.23, respectively), while *Business Sophistication* is associated with the lowest ones (0.16 and 0.14, respectively). Therefore, our results indicate that an increase in *Human Capital & Research* or *Infrastructure* is expected to yield higher returns compared to other input pillars. We also find that the sensitivities of the *Creative Outputs* pillar are higher than those of the *Knowledge & Technology* pillar, suggesting a greater response of the former to changes in innovation inputs.

We do not observe any patterns in the relationship between innovation inputs and sensitivities, given the respective low rank correlations in Table 3.[15] This implies that the extent to which further investments in innovation are expected to generate the desirable returns, does not depend on how well-resourced a country currently is. On the contrary, there is a close link between input endowments and the GII scores, suggesting that well-resourced economies are ranked highly in the GII report. Some exceptions are observed, though, where GII rankings are not necessarily in line with rankings based on input pillars. For example, Kuwait (KW) ranks in the middle-five countries in the GII report, despite exhibiting one of the smallest input values in the *Business Sophistication* pillar, while the opposite is observed for Niger (NE), further adding to the diversity of innovation systems. The high rank correlation between GII scores and input pillars, thus, highlights that, if policy aimed at achieving high GII scores, only countries with economies strong enough to invest heavily in innovation inputs would be able to achieve such a goal. However, such investments in innovation inputs may not generate the desirable returns, given our earlier findings on sensitivity for these countries. Taking also into account the low

[14] Since the GII score is the average of the Innovation Input Sub-Index and the Innovation Output Sub-Index, greater values in innovation inputs and outputs are associated with a higher score for the index by definition.

[15] Analytical results can be found in the accompanying Supplement.

rank correlation between sensitivities and GII scores, we confirm that it is not necessary for highly-ranked countries in the GII report to be as responsive to innovation investments. This reveals further considerations when using the GII scores for performance assessment or policy-making. Similar observations can be made when considering the rank correlations between innovation efficiency and the GII scores. Finally, the low rank correlations between innovation efficiency and sensitivity suggest that they offer additional and independent insights to the GII index, as well as that well-resourced economies are not necessarily responsible to innovation investments. While there is not necessarily adequate coverage of these points in the literature, we could state that our results are somewhat in contrast with the seminal paper of Furman, Porter, & Stern (2002) who find a positive link between R&D resourcing and R&D productivity. They certainly present an opportunity for future research, though.

Table 3. Summary of findings

	Institutions	Human Capital & Research	Infrastructure	Market Sophistication	Business Sophistication
Median Sensitivity (K&T)	0.14	0.30	0.23	0.15	0.12
Median Sensitivity (Cr)	0.21	0.43	0.31	0.22	0.13
Rank Corr: Sens (K&T) with Inputs	0.20	0.29	0.02	0.13	0.40
Rank Corr: Sens (Cr) with Inputs	-0.01	0.05	0.01	0.04	0.43
Rank Corr: Inputs with GII score	0.88	0.88	0.90	0.77	0.78
Rank Corr: Sens (K&T) with GII	0.16	0.20	-0.06	0.17	0.27
Rank Corr: Sens (Cr) with GII	-0.04	0.03	-0.07	0.03	0.32
Rank Corr: In.Eff with GII score	0.31	0.23	0.27	0.36	0.30
Rank Corr: In.Eff with Sens (K&T)	0.08	0.04	-0.09	0.03	0.06
Rank Corr: In.Eff with Sens (Cr)	0.00	0.00	-0.10	-0.02	0.08

Notes: The table summarizes the findings of our proposed framework. The first two rows exhibit the median values of the sensitivities for the *Knowledge & Technology* (K&T) and *Creative outputs* (Cr), against changes in the five innovation inputs (columns 2 to 6). Rows 3 and 4 present the rank correlations between the innovation inputs and the respective estimated sensitivities for the two innovation outputs. Rows 5 to 7 present the rank correlations of the GII scores with the innovation inputs and the estimated sensitivities for the two innovation outputs. The last three rows report the rank correlations between innovation efficiency and the GII scores as well as the respective estimated sensitivities.

We now consider innovation efficiency and sensitivity in combination to propose tailored innovation policies for each country.[16] In the figures below, we use color shading to identify three directions. The

[16] It is important to note that it is common in the literature of innovation efficiency to consider lagged responses of innovation outputs to innovation inputs (Cruz-Cázares et al., 2013). While we acknowledge this important consideration, the nature of the data used in the paper, imposes significant challenges and limitations associated with comparisons over time (GII, 2016, p. 58). However, after introducing certain adjustments and under the (strong) assumption that the variables composing the input and output pillars are unaffected, we present the results of our cross-period exercise in Figures S6 and S7 of the accompanying

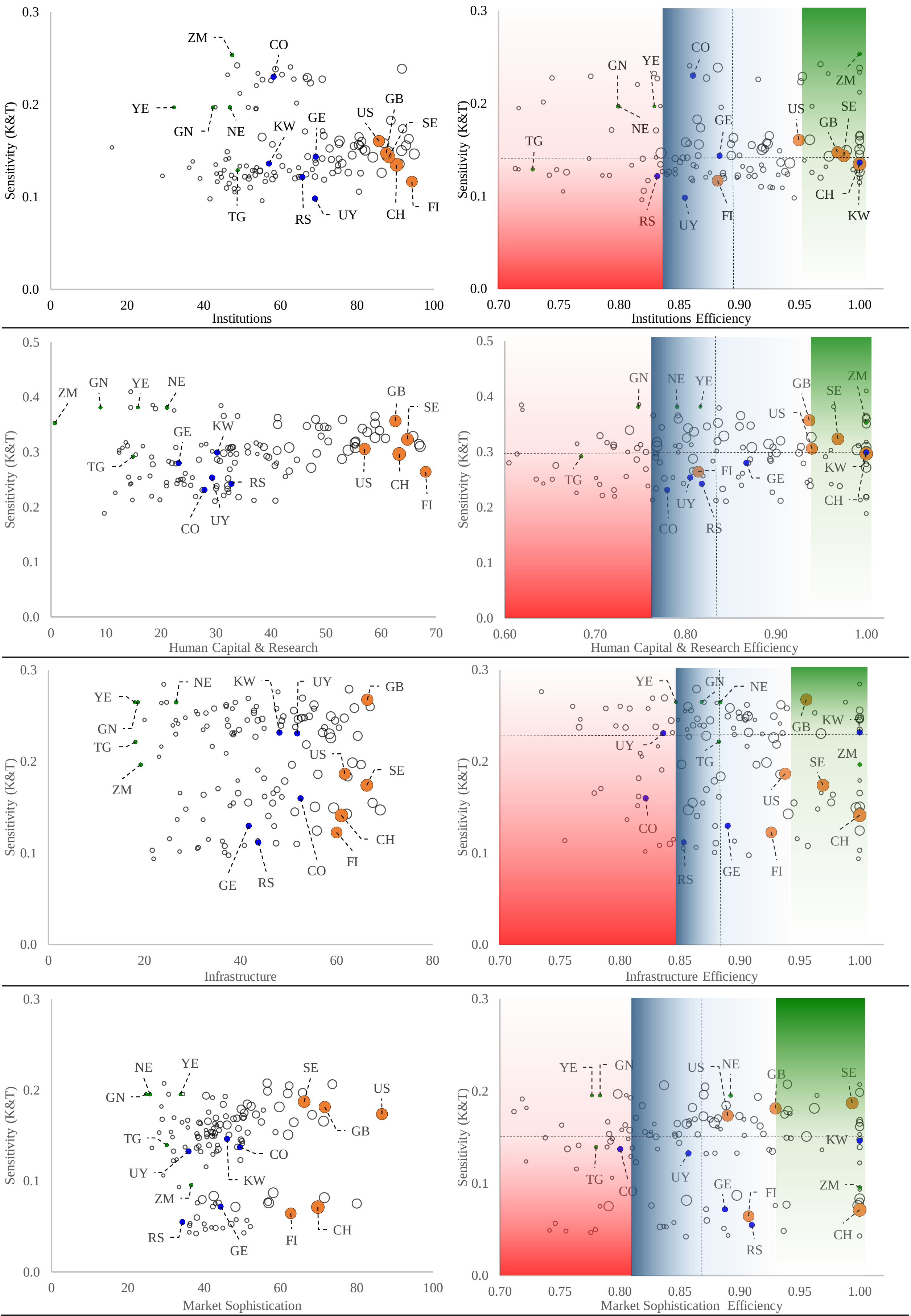
red shaded areas include countries ranked at the bottom quartile of the innovation efficiency in the respective input, implying a considerable potential for resource misallocation. The color scaling changes from dark to light red at the point that corresponds to the median sensitivity in the innovation input-output combination under consideration. The darker the red color, the lower the responsiveness to innovation inputs. Given also the substantial level of inefficiency, an increase in innovation inputs would probably mean that the used resources would generate less than expected innovation outputs. Even if countries are associated with high sensitivity, the possibility of substantial resource misallocation cannot be disregarded. Hence, policy makers should prioritize improving inefficiencies for countries in the red-shaded area by designing *innovation-improving* policies, as we call in this paper. The exact nature of these policies will depend on the structural characteristics of the countries concerned. For example, policymakers could adjust patent length to achieve an optimal balance between size and frequency of innovation (Horowitz & Lai, 1996). Similarly, Anderlini, Felli, Immordino, & Riboni (2013) show that relaxing legal system rigidities for countries at intermediate stages of technological development can increase the amount of innovations. Furthermore, Brown & Martinsson (2018) find that transparent information environments are associated with higher rates of R&D and patenting due to reducing information costs associated with financing.

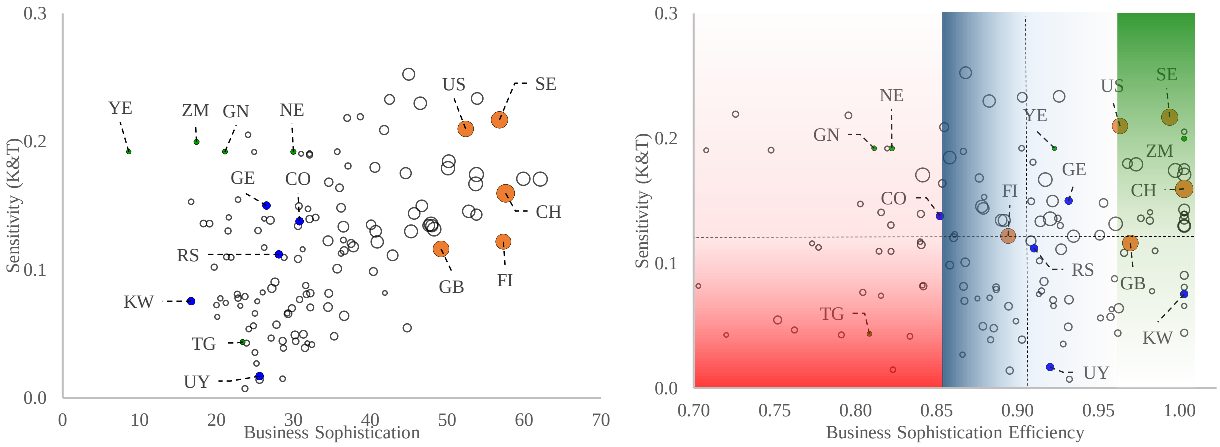
Countries in the top quartile are depicted with the green-shaded area in each input pillar. The median sensitivities are used again as the reference point for changing color grading, so that darker green is associated with greater responsiveness to innovation input expansions. Countries in the dark green area would therefore benefit from policies that promote and support innovation-related investments, which we henceforth refer to as *innovation-facilitating* policies. The business innovation policies in OECD (2011) belong in this category and examples include initiatives such as grants for basic research (Salter & Martin, 2001), R&D subsidies (Almus & Czarnitzki, 2003), or R&D tax credits (Wilson, 2009), among others.

Finally, countries between the first and fourth quartiles are depicted with the blue-shaded areas. In this case, the color scaling changes with respect to the median efficiency of the respective pillar, to signify the different nature of policy considerations in this case. The inefficiencies found in these countries are not alarming, but they cannot be disregarded either. Therefore, the lighter the blue shading, the smaller is the (potential for) resource misallocation. Here, a balanced mix of the mentioned policies is more appropriate; we refer to this combination of policies as *hybrid*. The policy mix depends on the position of each country in the quartiles formed by the crossing dotted lines that correspond to the median efficiencies and sensitivities. Thus, countries with relatively high (low) levels in both sensitivity and innovation efficiency should focus more on *innovation facilitating* (*innovation improving*) policies.

Supplement, also explaining in detail the aforementioned assumptions and limitations. We find that our results on innovation efficiency and sensitivity are quite robust when the innovation outputs of 2018 are used instead of those of 2016, while any conclusions and policy implications arising from our current analysis remain unaffected.

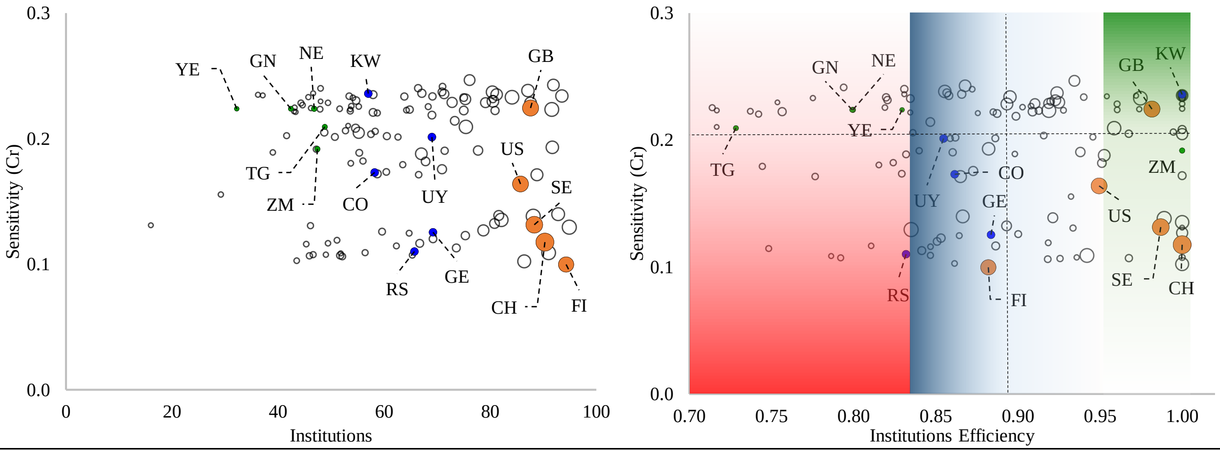
Figure 2. Sensitivities and MEA scores for *Knowledge & Technology Outputs*

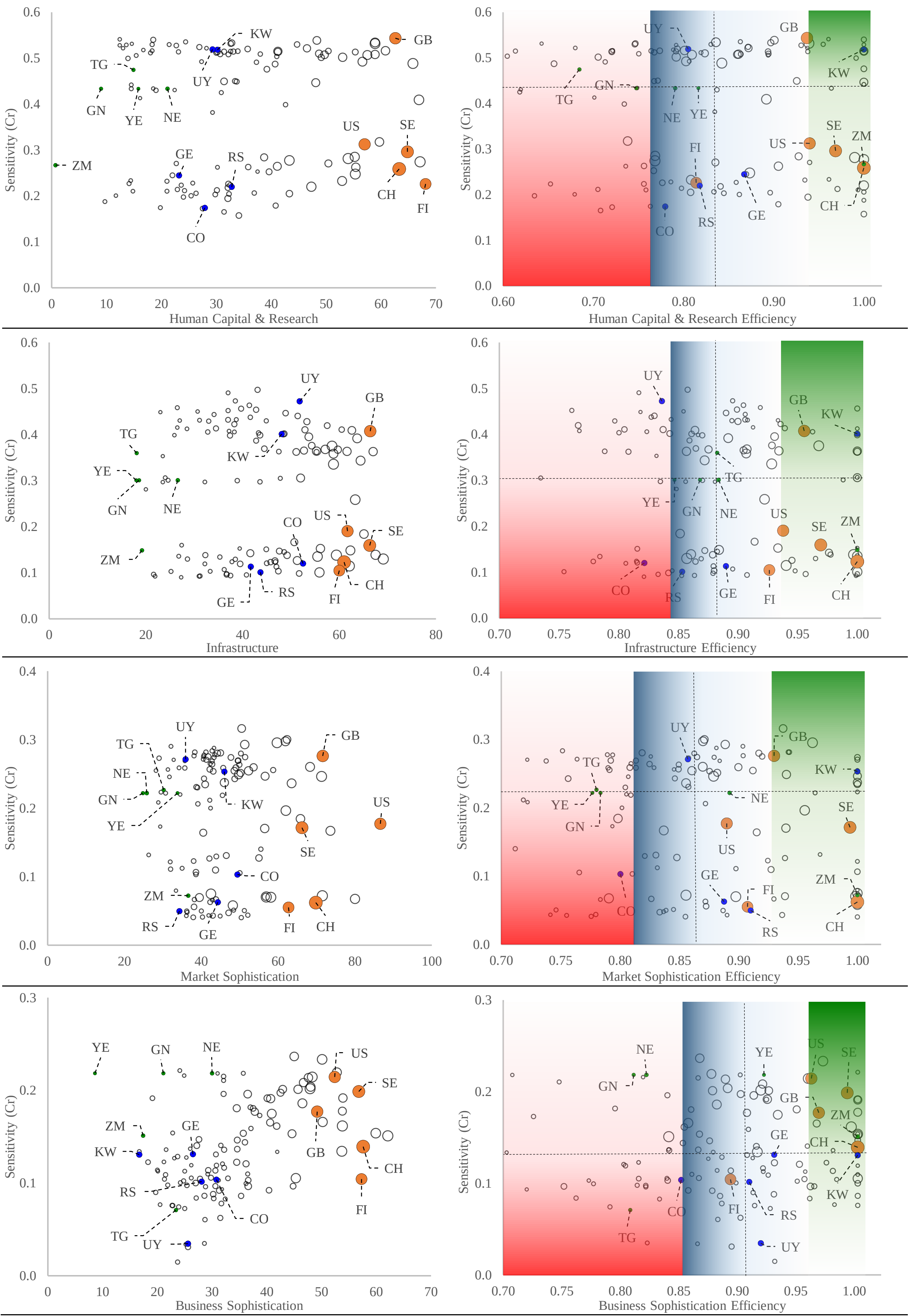




Notes: The first column of the figure plots the input pillar scores (vertical axis) against the sensitivity of *Knowledge & Technology Outputs* for the respective input (vertical axis). The second column presents the scatterplots of the sensitivities against the respective MEA efficiency scores (horizontal axis). The size of markers is proportional to countries' GII scores. The shaded areas provide an indication of the proposed innovation policy that a country should follow. The red-shaded areas correspond to the bottom MEA efficiency quartile for an innovation input, the green-shaded areas correspond to the top quartile, while the blue-shaded areas include the second and third MEA efficiency quartiles. The color grading in the red and green shaded areas changes at the median sensitivity of the respective pillar, while for the blue areas it changes at the median of the respective MEA scores. The horizontal dotted lines correspond to the median sensitivity, while the vertical ones correspond to the median efficiency. Finally, we highlight as example countries the top five (orange marker), bottom five (green marker) and middle five (blue marker) countries in the GII rankings. The full list of country abbreviations can be found in the accompanying Supplement.

Figure 3. Marginal contributions and MEA scores for *Creative Outputs*





Note: The figure exhibits the same information as in Figure 1, with the difference that the sensitivities are estimated with respect to *Creative Outputs*. Please refer to the notes in Figure 2 for further details.

In line with our findings on rank correlations, we observe that countries with a high GII score (the sizeable markers) are not necessarily located in the *innovation-facilitating* zone, meaning that an expansion of innovation inputs does not guarantee an efficient or productive use of resources. Similarly, there are examples of countries with a low GII score that are not necessarily in the *innovation-improving* area. For example, out of the top five countries in the GII rankings, only Great Britain (GB) appears consistently in the darker green area (with one marginal exception). Switzerland (CH) and Sweden (SE) also appear consistently within the green region, but the fact that they exhibit mostly below-median sensitivities indicates that they have reached a near-optimal level of innovation activity in the respective dimensions. Hence, although there are no concerns for resource misallocation, further input expansions will be subject to diminishing returns for these countries. Finland (FE) appears in the lower quadrants of the *hybrid* region and should focus on rectifying inefficiencies to improve its innovation performance.

Similar discussion can be made for middle and low-ranked countries in the GII report. Zambia (ZM) and Kuwait (KW) are examples among several low and medium-ranked countries located at the top quartile of efficiency and are therefore better suited for *innovation-facilitating* policies. Out of the five countries in the bottom of the GII ranking, only Togo (TG) and Guinea (GN) are located in the red area in all input pillars, except for *Infrastructure*. Therefore, *innovation-improving* policies need to be prioritized over any other innovation-related effort for these countries. On the contrary, Niger (NE) is more frequently located in the *hybrid* section, and, in fact, in the top-right quadrant for *Infrastructure* and *Market Sophistication* with respect to *Knowledge & Technology* outputs. Hence, providing more resources in this direction, coupled with monitoring systems to ensure a more efficient resource utilization, will yield positive innovation outcomes.

The high rank correlations between innovation efficiency scores imply that most countries are located in a similar region across input-output combinations.[17] However, we find that several countries are located in different innovation policy areas across the ten possible efficiency-sensitivity combinations. Therefore, policy should tailor its approach for each country, based on its location on the mapping proposed above. For example, Yemen (YE) would need, in principle, to follow *innovation-improving* policies, especially with respect to *Market Sophistication*, whereas it has a good potential in the direction of *Business Sophistication*. Examining the components of the respective pillars, Yemen should focus on promoting knowledge-intensive employment and knowledge transfers, as well as improving innovation linkages. At the same time, it should address frictions, transactions costs and other sources of inefficiency in the process of credit creation, in its investment environment, as well as in maintaining a healthy level of competition in the market.

Our findings, apart from proposing a reconsideration and expansion of the current framework that is used to assess countries' rankings, also carries important policy implications that even challenge

[17] To conserve space, we report the rank correlations of innovation efficiency scores in Table S6 of the Supplement.

statements found in the GII report. The first such statement relates to the claimed innovation divide between high and low-income countries (GII, 2016, p. xxiv). We show that the misallocation of resources is also possible in highly ranked countries, and that even lower-income countries can strike a balance between innovation efficiency and sensitivity. Therefore, the innovation divide may appear overstated when considering more dimensions in the analysis. The second such statement characterizes an entire region (Latin America and the Caribbean) as having an "untapped innovation potential" (GII, 2016, p. xxvi), but without providing supporting evidence. Our results show that most countries in Latin America and the Caribbean require *innovation-improving* policies, while only few cases can be found where *hybrid* policies could actually be implemented with an emphasis on *innovation-facilitating* ones. Finally, the responsiveness of LCN to innovation inputs is not always great, implying that not only resources may be misallocated but also that the wished outcomes are not necessarily feasible to achieve.

5. Conclusion

This paper introduces a two-step framework to identify the innovation policy direction that is most suitable for each country, while taking into account its environment. These policies are identified by joint consideration of countries' innovation efficiency and responsiveness to innovation-related investments. Our approach deals with two significant shortcomings of composite indicators, namely the fact that the diversity of national innovation systems (NIS) is not taken into account due to user-imposed weights and the counter-intuitive compensability property of the resulting composite indicators. Using data from the 2016 Global Innovation Index (GII) report, we highlight the diversity of NIS and propose tailored innovation policy directions, influenced by the extent to which the economic environment of each country is conducive to innovation. Our contribution is therefore twofold; not only do we propose a novel and flexible methodology that can be applied in various contexts, but we also use it to design an innovation policy toolbox that assesses the needs and comparative advantages of each country more accurately compared to current practices.

Two research objectives are evaluated regarding countries' innovation efficiency and sensitivity. The first one relates to the diversity of NIS, which, as expected, is confirmed. Using the MEA model, we obtain individual efficiency scores for each innovation pillar and identify substantial asymmetries. Evidence such as the fact that low-income countries appear significantly more inefficient with respect to *Creative Outputs* compared to *Knowledge & Technology* confirms that national priorities for innovation vary widely. Moreover, the fact that high-income countries in Europe perform better than their counterparts elsewhere, is also indicative of the role that local characteristics play on innovation, but also of the importance of market openness in facilitating knowledge transfers.

The second objective concerns the sensitivity that countries exhibit to changes in their innovation inputs, in relation to their peers. To estimate this, we propose a novel approach that runs separate (local) PLS regressions for each country, whereby the response and explanatory matrices correspond to the reference country's nearest neighbors (peers). Economic proximity is determined in our study by three economic variables, which could be easily modified to include other quantitative or qualitative ones. Hence, we offer a tool for the designing of targeted and feasible innovation policies, which is also flexible for policy experimentation. The most responsive input factor appears to be, on average, *Human Capital & Research* and to a smaller extent *Infrastructure*, whereas *Business Sophistication* seems to be the innovation input that influences innovation outputs the least. However, this pattern does not apply universally, due to the diversity that is also manifested in the sensitivity estimates.

The rankings in innovation efficiency and the estimated sensitivities have little relevance with the GII rankings, which means that we add two independent and intuitive dimensions to the empirical analysis of innovation. Using these two dimensions in combination, we propose three policies on the basis of the potential for resource misallocation (proxied by the innovation inefficiencies) and the expected response to further investments in innovation inputs: *innovation-facilitating*, *innovation-improving*, and *hybrid*. We observe that certain countries require a mixed approach, whereby *innovation-facilitating* policies may be suitable in one innovation input-output dimension, whereas *hybrid* or *innovation-facilitating* ones may be more suitable in another (or vice versa).

Our findings carry implications which should be of interest to policy makers who use composite indicators to inform their actions. First, the evaluation of countries' ability to innovate should not be based on simplistic approaches and should consider the influences of the environment which may be unique to each country. Characterizing countries as 'achievers', 'followers' and 'underperformers' without accounting for their environment can lead to potentially falsely identified innovation gaps between countries. Second, taking into account both innovation efficiency and sensitivity is necessary to avoid mistakes in the evaluation of countries' potential to innovate and hence mitigate the risk of resource misallocation. Finally, given the diversity of national innovation systems, it is imperative that innovation policy should be tailored for each country, instead of adopting a one-size-fits-all approach that composite indicators tend to promote.

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Supplement

A data envelopment analysis and local partial least squares approach for identifying the optimal innovation policy direction

Panagiotis Tziogkidis, Dionisis Philippas, Alexandros Leontitsis, and Robin C. Sickles

Figure S1. Innovation Input and Output pillars and Innovation Efficiency Ratio

The figure presents the Innovation Input and Output sub-indices for each region and the world, along with the respective pillars. The secondary axis demonstrates the respective Innovation Efficiency Ratios (IERs). Regions follow the United Nations classification, denoted as: Central and Southern Asia (CSA), Europe (EUR), Latin America and the Caribbean (LCN), Northern America (NAC), Northern Africa and Western Asia (NAWA), South East Asia and Oceania (SEAO) and Sub-Saharan Africa (SSF).

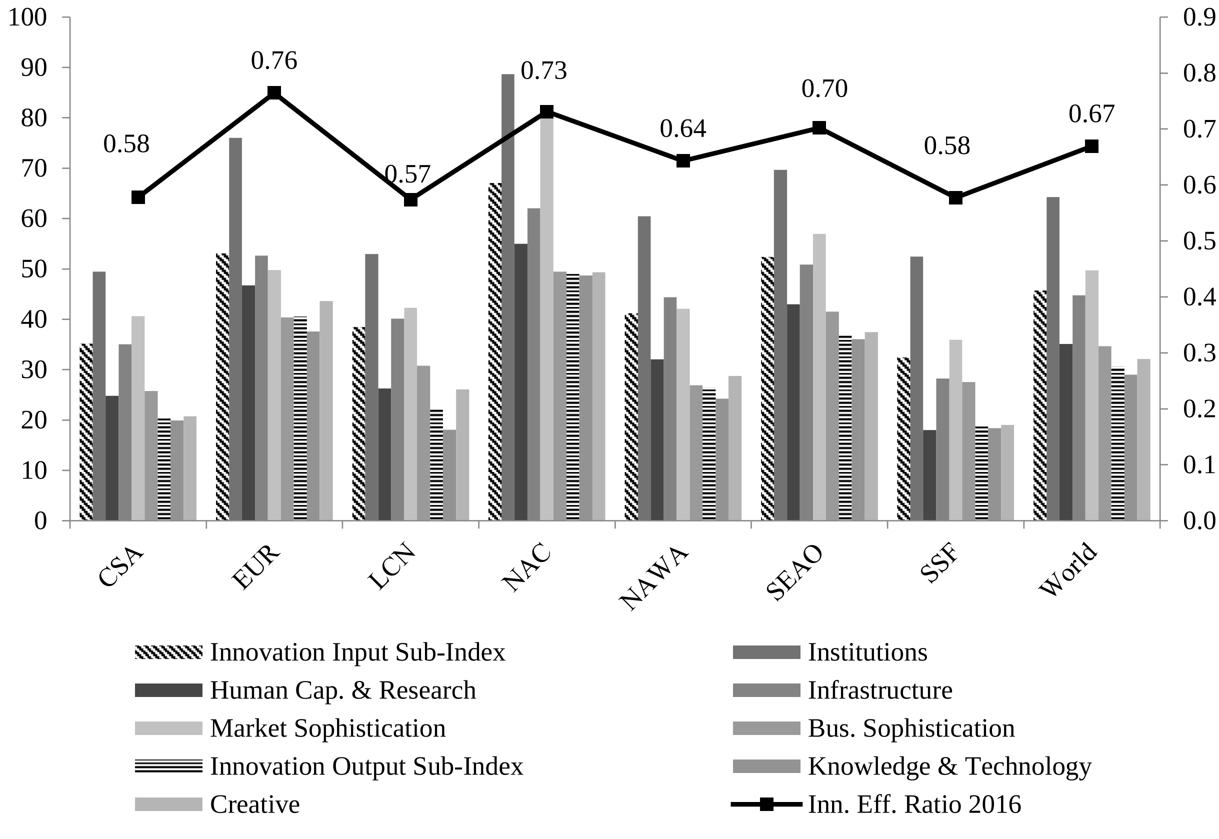


Figure S2. Innovation efficiency frontier

The Innovation Efficiency Ratio (IER) ranking in the official GII (2016) report is a benchmarking exercise which implies the existence of an innovation frontier defined by the most efficient country, which is Luxemburg (LU). The distance of each country from the frontier is related to its inefficiency relative to the benchmark. The figure plots the Innovation Input and Output sub-indices for all countries and regions and depicts the innovation efficiency frontier with the black dotted line. Countries of different regions are illustrated as follows: Central and Southern Asia (CSA) with blue gridded rhombi; European (EUR) countries with striped squares; Northern American (NAC) with pale orange crossed squares; South East Asia and Oceania (SEAO) with orange circles and black dots on a white background; Latin America and Caribbean (LCN) with green triangles; Northern Africa and Western Asia (NAWA) with red asterisks; and Saharan Africa (SSF) with blue crosses. The regional and global averages are depicted with a black transparent dot. Country name abbreviations can be found in Table S8 in this Supplement.

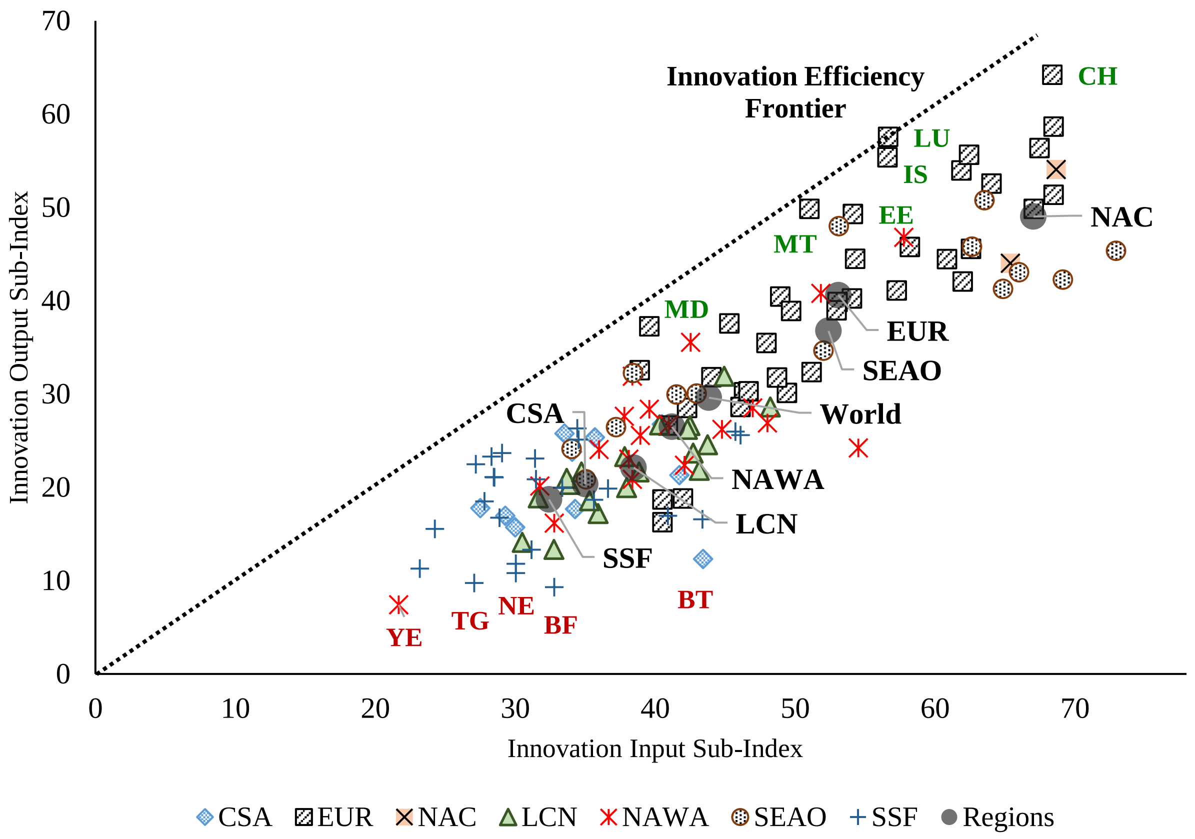
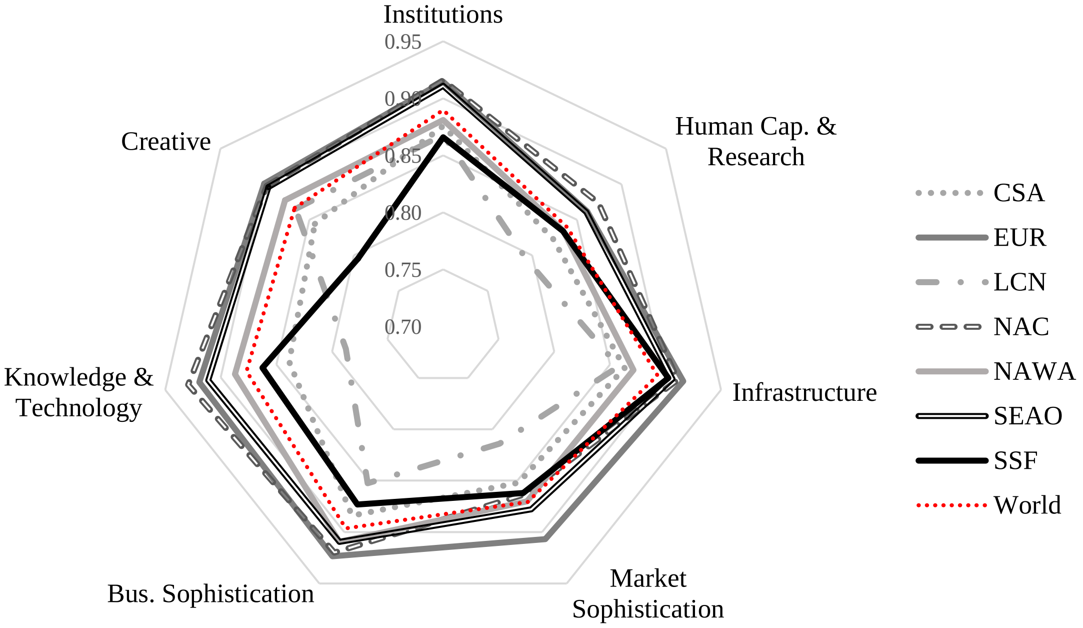


Figure S3. MEA innovation efficiency scores per region and income group

The figure presents the average relative efficiency scores per region (lower section) and per income group (lower section) for each innovation input and output, as estimated by MEA. Regions are denoted as: Central and Southern Asia (CSA), Europe (EUR), Latin America and the Caribbean (LCN), Northern America (NAC), Northern Africa and Western Asia (NAWA), South East Asia and Oceania (SEAO) and Sub-Saharan Africa (SSF). Income groups and regions follow the United Nations 2016 classification.



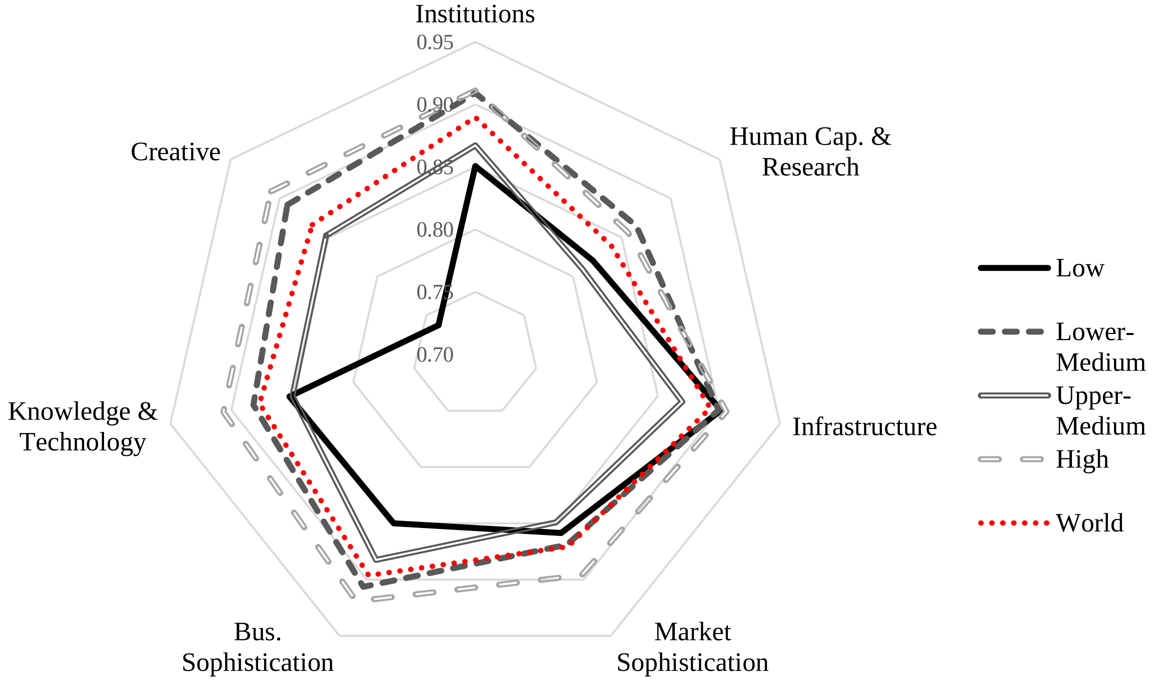


Table S1. Innovation efficiency colormap

The table presents analytical efficiency results for each country. Columns 2 to 6 present the relative efficiency scores by country for each input as calculated by MEA, namely *Institutions*, *Human Capital & Research*, *Infrastructure*, *Market Sophistication* and *Business Sophistication*. Columns 7 and 8 present the relative efficiency scores by country for each innovation output, namely *Knowledge & Technology* and *Creative Outputs*. Column *Eff(*ρ_k*)* presents the aggregated MEA efficiency scores by country, using the equation in footnote 4. The dark grey color is used to denote the bottom quartile, the patterned grey shading corresponds to the lower-middle quartile, the patterned light grey shading is used for the upper-middle quartile, while the light gray reflects the top quartile. Income groups follow the United Nations 2016 classification.

	Institutions	*Human Capital & Research*	*Infrastructure*	*Market Sophistication*	*Business Sophistication*	*Knowledge & Technology*	*Creative*	*ρk*
Central & Southern Asia								
Low								
Nepal	0.83	0.79	0.87	0.85	0.84	0.85	0.79	0.68
Lower-Middle								
Bangladesh	0.88	0.79	0.85	0.83	0.87	0.88	0.81	0.71
Bhutan	0.74	0.62	0.73	0.72	0.74	0.11	0.67	0.14
India	0.89	0.86	0.91	0.86	0.92	0.95	0.81	0.77
Kyrgyzstan	0.81	0.74	0.81	0.78	0.88	0.90	0.83	0.69
Pakistan	0.95	0.94	0.91	0.88	0.91	0.96	0.91	0.86
Sri Lanka	0.96	0.95	0.89	0.90	0.95	0.97	0.96	0.90
Tajikistan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Upper-Middle								
Iran, Islamic Republic of	0.93	0.83	0.88	0.89	0.91	0.93	0.91	0.82
Kazakhstan	0.78	0.71	0.78	0.81	0.82	0.83	0.76	0.62
Europe								
Lower-Middle								
Moldova, Republic of	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ukraine	0.97	0.91	0.98	0.94	0.98	0.98	0.97	0.93
Upper-Middle								
Albania	0.75	0.65	0.75	0.75	0.81	0.80	0.70	0.55
Belarus	0.82	0.73	0.83	0.87	0.88	0.91	0.43	0.48
Bosnia and Herzegovina	0.74	0.60	0.80	0.74	0.76	0.74	0.69	0.52
Bulgaria	0.95	0.94	0.95	0.93	0.95	0.96	0.96	0.90
Montenegro	0.85	0.76	0.86	0.83	0.85	0.78	0.83	0.67
Romania	0.90	0.89	0.89	0.92	0.93	0.95	0.91	0.84
Russian Federation	0.86	0.77	0.86	0.88	0.86	0.90	0.81	0.72
Serbia	0.83	0.82	0.85	0.91	0.91	0.93	0.81	0.75
The Former Yugoslav Republic (FYR) of Macedonia	0.86	0.77	0.94	0.85	0.90	0.82	0.93	0.75
High								
Austria	0.89	0.80	0.91	0.89	0.89	0.90	0.87	0.78
Belgium	0.92	0.86	0.93	0.94	0.92	0.95	0.91	0.85
Croatia	0.86	0.79	0.86	0.85	0.86	0.85	0.84	0.71
Czech Republic	0.93	0.90	0.93	0.94	0.92	0.95	0.92	0.87
Denmark	0.92	0.84	0.93	0.88	0.92	0.92	0.91	0.82
Estonia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Finland	0.88	0.81	0.93	0.91	0.89	0.93	0.87	0.80
France	0.92	0.84	0.89	0.87	0.89	0.89	0.91	0.79
Germany	0.97	0.94	0.97	0.96	0.96	0.97	0.97	0.93
Greece	0.87	0.72	0.84	0.81	0.91	0.84	0.92	0.73
Hungary	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Iceland	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ireland	0.99	0.99	1.00	1.00	0.99	1.00	0.99	0.99
Italy	0.92	0.87	0.88	0.90	0.91	0.93	0.90	0.82
Latvia	0.94	0.93	0.93	0.91	0.96	0.94	0.96	0.89
Lithuania	0.85	0.71	0.84	0.82	0.86	0.78	0.85	0.66
Luxembourg	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Malta	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Netherlands	0.94	0.87	0.94	0.90	0.91	0.91	0.94	0.84
Norway	0.87	0.79	0.86	0.86	0.88	0.86	0.86	0.73
Poland	0.85	0.77	0.87	0.83	0.87	0.83	0.86	0.71
Portugal	0.91	0.82	0.90	0.88	0.95	0.88	0.95	0.82
Slovakia	0.91	0.90	0.90	0.92	0.93	0.93	0.92	0.84
Slovenia	0.89	0.84	0.91	0.92	0.90	0.92	0.89	0.81
Spain	0.92	0.86	0.86	0.87	0.91	0.93	0.91	0.82
Sweden	0.99	0.97	0.97	0.99	0.99	1.00	0.96	0.96
Switzerland	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
United Kingdom	0.98	0.94	0.96	0.93	0.97	0.97	0.98	0.93
Latin America & Caribbean								
Lower-Middle								
Bolivia, Plurinational State of	0.93	0.83	0.86	0.80	0.86	0.87	0.93	0.77
El Salvador	0.82	0.72	0.82	0.76	0.82	0.58	0.83	0.54
Guatemala	0.87	0.82	0.92	0.79	0.83	0.84	0.90	0.74
Honduras	0.86	0.76	0.85	0.76	0.77	0.71	0.85	0.62
Nicaragua	0.79	0.68	0.82	0.74	0.77	0.66	0.76	0.54
Upper-Middle								
Argentina	0.84	0.71	0.80	0.79	0.80	0.74	0.82	0.61
Brazil	0.83	0.76	0.82	0.82	0.79	0.81	0.76	0.63
Colombia	0.86	0.78	0.82	0.80	0.85	0.82	0.84	0.68
Costa Rica	0.89	0.84	0.88	0.87	0.86	0.86	0.88	0.76
Dominican Republic	0.88	0.84	0.87	0.81	0.86	0.84	0.91	0.74
Ecuador	0.91	0.83	0.84	0.79	0.90	0.74	0.92	0.70
Jamaica	0.79	0.71	0.86	0.78	0.82	0.72	0.82	0.61
Mexico	0.86	0.77	0.86	0.81	0.86	0.83	0.84	0.70
Panama	0.90	0.87	0.88	0.87	0.91	0.91	0.91	0.80
Paraguay	0.93	0.86	0.91	0.81	0.93	0.67	0.94	0.69
Peru	0.83	0.72	0.82	0.77	0.81	0.68	0.81	0.58
Venezuela, Bolivarian Republic of	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
High								
Chile	0.84	0.78	0.84	0.83	0.84	0.82	0.81	0.68
Uruguay	0.85	0.81	0.84	0.86	0.92	0.86	0.92	0.76
Northern America								
High								
Canada	0.88	0.81	0.88	0.84	0.88	0.88	0.86	0.75
United States of America	0.95	0.94	0.94	0.89	0.96	0.98	0.94	0.90

Northern Africa & Western Asia								
Lower-Middle								
Armenia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Egypt	0.90	0.81	0.82	0.83	0.88	0.89	0.88	0.75
Morocco	0.92	0.90	0.88	0.92	0.97	0.95	0.98	0.88
Tunisia	0.84	0.75	0.83	0.86	0.88	0.87	0.87	0.72
Yemen	0.83	0.82	0.85	0.78	0.92	0.94	0.56	0.59
Upper-Middle								
Algeria	0.78	0.68	0.77	0.81	0.81	0.83	0.67	0.57
Azerbaijan	0.85	0.80	0.83	0.78	0.91	0.85	0.92	0.74
Georgia	0.88	0.87	0.89	0.89	0.93	0.94	0.89	0.82
Jordan	0.86	0.86	0.87	0.90	0.92	0.92	0.92	0.81
Lebanon	0.92	0.84	0.91	0.86	0.88	0.84	0.91	0.77
Turkey	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
High								
Bahrain	0.83	0.79	0.81	0.86	0.84	0.86	0.79	0.68
Cyprus	0.92	0.93	0.98	0.94	0.96	0.98	0.96	0.92
Israel	0.95	0.91	0.93	0.94	0.92	0.95	0.95	0.88
Kuwait	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Oman	0.79	0.76	0.79	0.80	0.92	0.84	0.93	0.72
Qatar	0.83	0.75	0.80	0.82	0.89	0.77	0.89	0.68
Saudi Arabia	0.89	0.75	0.83	0.79	0.88	0.78	0.88	0.69
United Arab Emirates	0.76	0.66	0.77	0.76	0.75	0.65	0.67	0.49
South East Asia & Oceania								
Lower-Middle								
Cambodia	0.92	0.86	0.95	0.85	0.86	0.92	0.91	0.81
Indonesia	0.95	0.94	0.90	0.88	0.93	0.96	0.94	0.87
Mongolia	0.91	0.87	0.94	0.85	0.95	0.89	0.96	0.84
Philippines	0.94	0.93	0.90	0.94	0.96	0.98	0.90	0.88
Viet Nam	0.97	0.97	0.96	0.94	0.96	0.98	0.97	0.93
Upper-Middle								
China	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Malaysia	0.87	0.81	0.88	0.85	0.85	0.87	0.84	0.73
Thailand	0.92	0.89	0.90	0.86	0.88	0.92	0.90	0.81
High								
Australia	0.87	0.74	0.85	0.80	0.86	0.80	0.86	0.68
Hong Kong (China)	0.87	0.77	0.86	0.79	0.86	0.81	0.84	0.68
Japan	0.86	0.81	0.87	0.87	0.87	0.90	0.79	0.72
Korea, Republic of	0.96	0.89	0.92	0.96	0.97	0.98	0.95	0.91
New Zealand	0.90	0.80	0.91	0.86	0.93	0.88	0.93	0.79
Singapore	0.84	0.77	0.86	0.86	0.84	0.87	0.76	0.67
Sub-Saharan Africa								
Low								
Benin	0.72	0.62	0.85	0.72	0.70	0.67	0.80	0.53
Burkina Faso	0.72	0.70	0.83	0.79	0.70	0.82	0.09	0.13
Burundi	0.75	0.64	0.82	0.72	0.72	0.52	0.77	0.46
Ethiopia	0.97	0.96	0.97	0.97	0.98	0.97	0.98	0.95
Guinea	0.80	0.75	0.87	0.78	0.81	0.70	0.84	0.61
Madagascar	0.94	0.99	1.00	0.89	0.98	0.99	1.00	0.96
Malawi	0.96	0.96	0.99	0.96	0.90	0.98	0.98	0.94

Mali	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mozambique	0.93	0.94	0.97	0.93	0.91	0.98	0.91	0.88
Niger	0.80	0.79	0.88	0.89	0.82	0.91	0.04	0.06
Rwanda	0.74	0.63	0.78	0.71	0.72	0.63	0.66	0.46
Senegal	0.90	0.89	0.91	0.90	0.92	0.92	0.86	0.81
Tanzania, United Republic of	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Togo	0.73	0.68	0.88	0.78	0.81	0.88	0.32	0.36
Uganda	0.82	0.76	0.81	0.83	0.80	0.81	0.75	0.63
Lower-Middle								
Cameroon	0.83	0.75	0.88	0.81	0.82	0.82	0.82	0.67
Cote d'Ivoire	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ghana	0.85	0.79	0.84	0.84	0.84	0.86	0.78	0.68
Kenya	0.99	0.99	0.96	0.94	0.96	0.99	0.99	0.96
Nigeria	0.97	0.96	0.93	0.88	0.96	0.98	0.97	0.92
Zambia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Upper-Middle								
Botswana	0.71	0.61	0.76	0.75	0.79	0.78	0.63	0.51
Mauritius	0.82	0.77	0.86	0.81	0.89	0.86	0.89	0.73
Namibia	0.86	0.93	0.90	0.84	0.98	0.63	0.99	0.70
South Africa	0.82	0.72	0.87	0.79	0.84	0.84	0.80	0.66

Table S2. Economic variables

The table presents the average values for R&D as a percentage of GDP, Foreign Direct Investment (FDI) inflows as a percentage of GDP, and the trade openness for each economic group within each region per region and economic income. The sample comes from the World Bank database. The table reports substantial differences between regions as well as between similar income groups of different regions. Income groups follow the United Nations 2016 classification.

	R&D (% GDP)	FDI Inflows (% GDP)	Trade Openness
Central and Southern Asia	**0.33**	**3.81**	**0.55**
Low	0.30	0.24	0.53
Lower–Middle	0.36	4.20	0.59
Upper–Middle	0.25	4.20	0.39
Europe	**1.44**	**6.58**	**1.17**
Lower–Middle	0.52	3.47	1.13
Upper–Middle	0.56	5.22	0.87
High	1.79	7.24	1.27
Latin America and the Caribbean	**0.29**	**4.30**	**0.54**
Lower–Middle	0.07	3.99	0.78
Upper–Middle	0.38	4.23	0.44
High	0.36	5.53	0.53
Northern America	**2.17**	**2.85**	**0.47**
High	2.17	2.85	0.47
Northern Africa and Western Asia	**0.60**	**4.21**	**0.81**
Lower–Middle	0.57	1.84	0.62
Upper–Middle	0.34	4.90	0.78
High	0.80	5.17	0.97
South East Asia and Oceania	**1.33**	**8.06**	**1.24**
Lower–Middle	0.14	4.13	1.00
Upper–Middle	1.26	2.75	1.01
High	2.36	13.99	1.56
Sub-Saharan Africa	**0.44**	**4.46**	**0.69**
Low	0.50	4.98	0.64
Lower–Middle	0.41	3.74	0.63
Upper–Middle	0.33	3.56	0.97

Tables S3a -S3g. Sensitivity of MEA scores

The tables below (one for each input-output variable) present the results of the bootstrap exercise that evaluates the sensitivity of MEA scores to sampling variations. We have used the *m/n* bootstrap since it is shown to be suitable for directional distance functions (Simar et al., 2012) and to avoid excessive computational costs we have determined the optimal block size (Politis et al., 2001) using a limited range of block sizes and *B*=500 replications (without replacement). The third column presents the MEA scores, the fourth column the bias-corrected MEA scores (Simar et al., 2012), the fifth column the bootstrap bias, the sixth column the estimated MEA standard error, while the last two columns report the resulting confidence intervals.

Table S3a. Bootstrap MEA results for Institutions

Country	Code	MEAeff	Bias-corrected	Bootstrap Bias	Std.Error	2.5% CI	97.5% CI
Albania	AL	0.748	0.745	0.003	0.020	0.717	0.777
Algeria	DZ	0.775	0.757	0.019	0.035	0.716	0.797
Argentina	AR	0.840	0.813	0.027	0.039	0.778	0.836
Armenia	AM	1.000	1.000	0.000	0.000	1.000	1.000
Australia	AU	0.865	0.844	0.021	0.033	0.807	0.867
Austria	AT	0.893	0.864	0.029	0.047	0.828	0.895
Azerbaijan	AZ	0.847	0.831	0.016	0.039	0.753	0.870
Bahrain	BH	0.831	0.818	0.013	0.026	0.788	0.846
Bangladesh	BD	0.876	0.858	0.018	0.039	0.799	0.888
Belarus	BY	0.824	0.796	0.028	0.051	0.732	0.860
Belgium	BE	0.925	0.896	0.029	0.042	0.879	0.924
Benin	BJ	0.717	0.700	0.016	0.030	0.668	0.736
Bhutan	BT	0.737	0.726	0.011	0.023	0.698	0.752
Bolivia, Plurinational State of	BO	0.932	0.901	0.031	0.043	0.891	0.927
Bosnia and Herzegovina	BA	0.742	0.723	0.019	0.031	0.696	0.750
Botswana	BW	0.714	0.702	0.012	0.028	0.668	0.745
Brazil	BR	0.832	0.814	0.018	0.031	0.779	0.844
Bulgaria	BG	0.951	0.931	0.020	0.030	0.921	0.954
Burkina Faso	BF	0.717	0.665	0.051	0.078	0.601	0.725
Burundi	BI	0.754	0.751	0.003	0.026	0.710	0.783
Cote d'Ivoire	CI	1.000	1.000	0.000	0.000	1.000	1.000
Cambodia	KH	0.918	0.887	0.032	0.048	0.869	0.919
Cameroon	CM	0.834	0.824	0.011	0.022	0.798	0.850
Canada	CA	0.882	0.867	0.016	0.025	0.837	0.887
Chile	CL	0.841	0.835	0.006	0.018	0.808	0.858
China	CN	1.000	1.000	0.000	0.000	1.000	1.000
Colombia	CO	0.862	0.852	0.009	0.021	0.822	0.874
Costa Rica	CR	0.886	0.860	0.026	0.048	0.817	0.898
Croatia	HR	0.857	0.843	0.014	0.025	0.810	0.866
Cyprus	CY	0.921	0.881	0.040	0.056	0.873	0.926
Czech Republic	CZ	0.934	0.908	0.027	0.037	0.894	0.933
Denmark	DK	0.919	0.896	0.022	0.035	0.869	0.922
Dominican Republic	DO	0.885	0.858	0.027	0.049	0.815	0.916
Ecuador	EC	0.908	0.882	0.026	0.045	0.852	0.921

Egypt	EG	0.898	0.879	0.019	0.030	0.849	0.901
El Salvador	SV	0.819	0.804	0.015	0.040	0.747	0.849
Estonia	EE	1.000	1.000	0.000	0.000	1.000	1.000
Ethiopia	ET	0.974	0.959	0.015	0.020	0.958	0.972
Finland	FI	0.882	0.845	0.037	0.056	0.810	0.880
France	FR	0.924	0.904	0.020	0.030	0.877	0.925
Georgia	GE	0.884	0.848	0.035	0.059	0.812	0.892
Germany	DE	0.975	0.960	0.014	0.019	0.959	0.973
Ghana	GH	0.847	0.831	0.016	0.030	0.797	0.864
Greece	GR	0.866	0.835	0.031	0.054	0.784	0.875
Guatemala	GT	0.872	0.842	0.030	0.051	0.794	0.897
Guinea	GN	0.799	0.763	0.036	0.089	0.676	0.835
Honduras	HN	0.861	0.844	0.017	0.033	0.809	0.884
Hong Kong (China)	HK	0.866	0.850	0.016	0.027	0.820	0.872
Hungary	HU	1.000	1.000	0.000	0.000	1.000	1.000
Iceland	IS	1.000	1.000	0.000	0.000	1.000	1.000
India	IN	0.886	0.844	0.042	0.062	0.817	0.897
Indonesia	ID	0.946	0.925	0.021	0.029	0.912	0.947
Iran, Islamic Republic of	IR	0.926	0.901	0.025	0.038	0.880	0.929
Ireland	IE	0.989	0.982	0.007	0.009	0.982	0.982
Israel	IL	0.953	0.927	0.026	0.034	0.924	0.951
Italy	IT	0.919	0.894	0.024	0.036	0.869	0.919
Jamaica	JM	0.792	0.788	0.004	0.019	0.757	0.813
Japan	JP	0.856	0.823	0.033	0.052	0.778	0.870
Jordan	JO	0.859	0.827	0.032	0.064	0.772	0.882
Kazakhstan	KZ	0.777	0.766	0.010	0.024	0.736	0.796
Kenya	KE	0.995	0.991	0.003	0.004	0.991	0.991
Korea, Republic of	KR	0.959	0.936	0.023	0.030	0.933	0.960
Kuwait	KW	1.000	1.000	0.000	0.000	1.000	1.000
Kyrgyzstan	KG	0.811	0.782	0.029	0.067	0.695	0.854
Latvia	LV	0.938	0.910	0.028	0.040	0.900	0.941
Lebanon	LB	0.918	0.894	0.024	0.039	0.868	0.922
Lithuania	LT	0.847	0.817	0.029	0.045	0.772	0.845
Luxembourg	LU	1.000	1.000	0.000	0.000	1.000	1.000
Madagascar	MG	0.936	0.896	0.039	0.050	0.896	0.896
Malawi	MW	0.960	0.937	0.023	0.030	0.936	0.951
Malaysia	MY	0.873	0.853	0.019	0.030	0.827	0.878
Mali	ML	1.000	1.000	0.000	0.000	1.000	1.000
Malta	MT	1.000	1.000	0.000	0.000	1.000	1.000
Mauritius	MU	0.821	0.815	0.006	0.027	0.778	0.853
Mexico	MX	0.862	0.849	0.013	0.023	0.821	0.872
Moldova, Republic of	MD	1.000	1.000	0.000	0.000	1.000	1.000
Mongolia	MN	0.913	0.884	0.029	0.049	0.859	0.923
Montenegro	ME	0.851	0.839	0.012	0.024	0.805	0.862
Morocco	MA	0.916	0.871	0.045	0.061	0.864	0.914
Mozambique	MZ	0.934	0.897	0.036	0.048	0.893	0.936
Namibia	NA	0.864	0.795	0.069	0.097	0.781	0.864
Nepal	NP	0.831	0.814	0.017	0.032	0.783	0.847

Netherlands	NL	0.942	0.918	0.024	0.035	0.907	0.942
New Zealand	NZ	0.895	0.859	0.036	0.056	0.831	0.898
Nicaragua	NI	0.786	0.793	-0.007	0.043	0.655	0.837
Niger	NE	0.800	0.756	0.043	0.073	0.677	0.825
Nigeria	NG	0.972	0.956	0.016	0.021	0.955	0.971
Norway	NO	0.868	0.847	0.020	0.038	0.787	0.877
Oman	OM	0.794	0.733	0.061	0.109	0.668	0.816
Pakistan	PK	0.954	0.932	0.022	0.030	0.926	0.958
Panama	PA	0.900	0.880	0.021	0.037	0.839	0.910
Paraguay	PY	0.928	0.899	0.029	0.045	0.883	0.936
Peru	PE	0.829	0.822	0.007	0.024	0.786	0.849
Philippines	PH	0.940	0.907	0.033	0.044	0.903	0.941
Poland	PL	0.853	0.837	0.016	0.028	0.802	0.859
Portugal	PT	0.910	0.872	0.038	0.056	0.855	0.912
Qatar	QA	0.835	0.821	0.013	0.034	0.757	0.855
Romania	RO	0.899	0.870	0.029	0.049	0.837	0.909
Russian Federation	RU	0.858	0.825	0.033	0.052	0.775	0.869
Rwanda	RW	0.744	0.745	-0.001	0.016	0.721	0.769
Saudi Arabia	SA	0.887	0.865	0.022	0.037	0.821	0.889
Senegal	SN	0.903	0.871	0.031	0.052	0.843	0.911
Serbia	RS	0.832	0.807	0.025	0.051	0.729	0.852
Singapore	SG	0.835	0.800	0.035	0.056	0.751	0.851
Slovakia	SK	0.909	0.889	0.020	0.037	0.853	0.920
Slovenia	SI	0.893	0.860	0.033	0.058	0.828	0.904
South Africa	ZA	0.820	0.812	0.007	0.019	0.786	0.838
Spain	ES	0.923	0.894	0.029	0.043	0.876	0.924
Sri Lanka	LK	0.960	0.941	0.020	0.027	0.936	0.959
Sweden	SE	0.987	0.979	0.008	0.010	0.979	0.982
Switzerland	CH	1.000	1.000	0.000	0.000	1.000	1.000
Tajikistan	TJ	1.000	1.000	0.000	0.000	1.000	1.000
Tanzania, United Republic of	TZ	1.000	1.000	0.000	0.000	1.000	1.000
Thailand	TH	0.920	0.900	0.020	0.030	0.871	0.924
The Former Yugoslav Republic (FYR) of Macedonia	MK	0.860	0.820	0.040	0.072	0.775	0.875
Togo	TG	0.728	0.672	0.057	0.095	0.562	0.732
Tunisia	TN	0.836	0.816	0.021	0.044	0.736	0.856
Turkey	TR	1.000	1.000	0.000	0.000	1.000	1.000
Uganda	UG	0.815	0.807	0.009	0.023	0.776	0.837
Ukraine	UA	0.968	0.950	0.017	0.023	0.948	0.965
United Arab Emirates	AE	0.757	0.750	0.007	0.018	0.722	0.771
United Kingdom	GB	0.982	0.971	0.010	0.014	0.970	0.979
United States of America	US	0.949	0.925	0.025	0.035	0.918	0.953
Uruguay	UY	0.855	0.838	0.017	0.042	0.766	0.874
Venezuela, Bolivarian Republic of	VE	1.000	1.000	0.000	0.000	1.000	1.000
Viet Nam	VN	0.968	0.950	0.018	0.024	0.948	0.966
Yemen	YE	0.830	0.765	0.064	0.111	0.725	0.877
Zambia	ZM	1.000	1.000	0.000	0.000	1.000	1.000

Table S3b. Bootstrap MEA results for Human Capital & Research

		Human Capital & Research					
Country	**Code**	**MEAeff**	**Bias-corrected**	**Bootstrap Bias**	**Std.Error**	**2.5% CI**	**97.5% CI**
Albania	AL	0.653	0.579	0.074	0.107	0.527	0.674
Algeria	DZ	0.680	0.639	0.041	0.062	0.593	0.691
Argentina	AR	0.713	0.693	0.020	0.040	0.643	0.737
Armenia	AM	1.000	1.000	0.000	0.000	1.000	1.000
Australia	AU	0.738	0.701	0.037	0.057	0.641	0.745
Austria	AT	0.801	0.754	0.047	0.081	0.679	0.812
Azerbaijan	AZ	0.798	0.742	0.056	0.083	0.674	0.803
Bahrain	BH	0.792	0.759	0.033	0.051	0.713	0.798
Bangladesh	BD	0.792	0.712	0.079	0.115	0.664	0.804
Belarus	BY	0.734	0.705	0.029	0.058	0.636	0.769
Belgium	BE	0.861	0.816	0.045	0.072	0.776	0.871
Benin	BJ	0.620	0.554	0.066	0.092	0.500	0.616
Bhutan	BT	0.618	0.564	0.055	0.081	0.508	0.625
Bolivia, Plurinational State of	BO	0.835	0.784	0.051	0.086	0.733	0.859
Bosnia and Herzegovina	BA	0.605	0.556	0.049	0.072	0.514	0.627
Botswana	BW	0.614	0.555	0.059	0.087	0.508	0.632
Brazil	BR	0.756	0.730	0.026	0.041	0.693	0.768
Bulgaria	BG	0.938	0.910	0.028	0.039	0.900	0.936
Burkina Faso	BF	0.701	0.602	0.099	0.141	0.519	0.705
Burundi	BI	0.643	0.556	0.086	0.129	0.482	0.655
Cote d'Ivoire	CI	1.000	1.000	0.000	0.000	1.000	1.000
Cambodia	KH	0.858	0.791	0.068	0.094	0.772	0.861
Cameroon	CM	0.749	0.692	0.056	0.083	0.639	0.765
Canada	CA	0.808	0.778	0.031	0.049	0.734	0.817
Chile	CL	0.777	0.740	0.037	0.059	0.686	0.790
China	CN	1.000	1.000	0.000	0.000	1.000	1.000
Colombia	CO	0.780	0.744	0.036	0.057	0.692	0.786
Costa Rica	CR	0.841	0.791	0.050	0.076	0.744	0.841
Croatia	HR	0.793	0.760	0.033	0.055	0.697	0.803
Cyprus	CY	0.928	0.887	0.041	0.054	0.883	0.922
Czech Republic	CZ	0.901	0.864	0.037	0.055	0.840	0.903
Denmark	DK	0.843	0.811	0.031	0.057	0.746	0.862
Dominican Republic	DO	0.837	0.782	0.055	0.082	0.737	0.834
Ecuador	EC	0.830	0.768	0.062	0.088	0.727	0.831
Egypt	EG	0.806	0.785	0.022	0.042	0.739	0.835
El Salvador	SV	0.722	0.637	0.084	0.124	0.556	0.722
Estonia	EE	1.000	1.000	0.000	0.000	1.000	1.000
Ethiopia	ET	0.961	0.939	0.022	0.029	0.938	0.958
Finland	FI	0.814	0.762	0.052	0.079	0.700	0.816
France	FR	0.836	0.812	0.024	0.044	0.735	0.849
Georgia	GE	0.867	0.805	0.063	0.085	0.786	0.859
Germany	DE	0.939	0.907	0.033	0.044	0.902	0.940
Ghana	GH	0.786	0.762	0.024	0.039	0.725	0.796
Greece	GR	0.721	0.663	0.058	0.103	0.549	0.752

Guatemala	GT	0.819	0.759	0.061	0.088	0.709	0.816
Guinea	GN	0.748	0.654	0.093	0.138	0.593	0.760
Honduras	HN	0.758	0.710	0.049	0.073	0.647	0.759
Hong Kong (China)	HK	0.769	0.741	0.028	0.047	0.687	0.778
Hungary	HU	1.000	1.000	0.000	0.000	1.000	1.000
Iceland	IS	1.000	1.000	0.000	0.000	1.000	1.000
India	IN	0.864	0.819	0.044	0.066	0.780	0.867
Indonesia	ID	0.938	0.916	0.021	0.032	0.900	0.941
Iran, Islamic Republic of	IR	0.834	0.792	0.042	0.077	0.732	0.865
Ireland	IE	0.990	0.984	0.006	0.008	0.984	0.984
Israel	IL	0.905	0.859	0.047	0.065	0.847	0.908
Italy	IT	0.872	0.839	0.033	0.054	0.794	0.882
Jamaica	JM	0.705	0.647	0.058	0.087	0.583	0.717
Japan	JP	0.809	0.782	0.028	0.047	0.723	0.823
Jordan	JO	0.862	0.812	0.050	0.076	0.777	0.875
Kazakhstan	KZ	0.708	0.663	0.045	0.065	0.623	0.720
Kenya	KE	0.991	0.986	0.005	0.007	0.986	0.986
Korea, Republic of	KR	0.892	0.839	0.053	0.076	0.826	0.908
Kuwait	KW	1.000	1.000	0.000	0.000	1.000	1.000
Kyrgyzstan	KG	0.736	0.669	0.067	0.108	0.574	0.773
Latvia	LV	0.926	0.891	0.035	0.049	0.880	0.932
Lebanon	LB	0.845	0.800	0.045	0.069	0.750	0.850
Lithuania	LT	0.705	0.652	0.054	0.081	0.578	0.706
Luxembourg	LU	1.000	1.000	0.000	0.000	1.000	1.000
Madagascar	MG	0.993	0.989	0.004	0.005	0.989	0.989
Malawi	MW	0.964	0.943	0.021	0.028	0.942	0.960
Malaysia	MY	0.808	0.784	0.023	0.038	0.748	0.818
Mali	ML	1.000	1.000	0.000	0.000	1.000	1.000
Malta	MT	1.000	1.000	0.000	0.000	1.000	1.000
Mauritius	MU	0.768	0.711	0.057	0.083	0.650	0.771
Mexico	MX	0.767	0.735	0.032	0.052	0.682	0.782
Moldova, Republic of	MD	1.000	1.000	0.000	0.000	1.000	1.000
Mongolia	MN	0.872	0.818	0.054	0.077	0.793	0.887
Montenegro	ME	0.756	0.718	0.039	0.063	0.651	0.765
Morocco	MA	0.896	0.841	0.055	0.075	0.832	0.892
Mozambique	MZ	0.940	0.907	0.033	0.044	0.903	0.940
Namibia	NA	0.935	0.897	0.037	0.049	0.895	0.935
Nepal	NP	0.789	0.730	0.059	0.085	0.667	0.792
Netherlands	NL	0.873	0.820	0.053	0.077	0.796	0.866
New Zealand	NZ	0.803	0.728	0.075	0.109	0.682	0.803
Nicaragua	NI	0.679	0.576	0.103	0.156	0.483	0.704
Niger	NE	0.791	0.728	0.062	0.102	0.663	0.814
Nigeria	NG	0.961	0.939	0.022	0.029	0.937	0.960
Norway	NO	0.792	0.754	0.038	0.065	0.665	0.804
Oman	OM	0.764	0.679	0.085	0.129	0.620	0.763
Pakistan	PK	0.937	0.907	0.030	0.042	0.899	0.938
Panama	PA	0.870	0.828	0.042	0.064	0.790	0.878
Paraguay	PY	0.863	0.799	0.064	0.089	0.779	0.862

Peru	PE	0.721	0.672	0.049	0.074	0.612	0.730
Philippines	PH	0.930	0.894	0.037	0.049	0.888	0.929
Poland	PL	0.767	0.727	0.040	0.062	0.664	0.770
Portugal	PT	0.824	0.744	0.079	0.112	0.716	0.834
Qatar	QA	0.747	0.690	0.057	0.090	0.604	0.761
Romania	RO	0.894	0.847	0.047	0.065	0.829	0.893
Russian Federation	RU	0.774	0.757	0.017	0.037	0.713	0.799
Rwanda	RW	0.635	0.573	0.062	0.092	0.522	0.657
Saudi Arabia	SA	0.746	0.716	0.030	0.053	0.653	0.768
Senegal	SN	0.894	0.845	0.049	0.067	0.829	0.893
Serbia	RS	0.818	0.771	0.047	0.072	0.707	0.827
Singapore	SG	0.768	0.738	0.030	0.049	0.688	0.780
Slovakia	SK	0.897	0.860	0.037	0.054	0.834	0.904
Slovenia	SI	0.835	0.784	0.051	0.089	0.735	0.847
South Africa	ZA	0.720	0.671	0.049	0.075	0.626	0.747
Spain	ES	0.860	0.811	0.049	0.077	0.774	0.876
Sri Lanka	LK	0.955	0.933	0.022	0.030	0.927	0.955
Sweden	SE	0.969	0.951	0.018	0.024	0.949	0.966
Switzerland	CH	1.000	1.000	0.000	0.000	1.000	1.000
Tajikistan	TJ	1.000	1.000	0.000	0.000	1.000	1.000
Tanzania, United Republic of	TZ	1.000	1.000	0.000	0.000	1.000	1.000
Thailand	TH	0.894	0.872	0.022	0.035	0.830	0.901
The Former Yugoslav Republic (FYR) of Macedonia	MK	0.772	0.688	0.083	0.125	0.632	0.775
Togo	TG	0.685	0.563	0.121	0.171	0.491	0.715
Tunisia	TN	0.750	0.717	0.034	0.069	0.598	0.787
Turkey	TR	1.000	1.000	0.000	0.000	1.000	1.000
Uganda	UG	0.763	0.709	0.054	0.078	0.651	0.769
Ukraine	UA	0.905	0.858	0.047	0.068	0.847	0.920
United Arab Emirates	AE	0.656	0.616	0.041	0.061	0.574	0.665
United Kingdom	GB	0.937	0.903	0.034	0.046	0.898	0.937
United States of America	US	0.940	0.910	0.030	0.041	0.903	0.939
Uruguay	UY	0.805	0.756	0.049	0.078	0.686	0.822
Venezuela, Bolivarian Republic of	VE	1.000	1.000	0.000	0.000	1.000	1.000
Viet Nam	VN	0.971	0.955	0.016	0.021	0.953	0.970
Yemen	YE	0.817	0.739	0.078	0.118	0.704	0.831
Zambia	ZM	1.000	1.000	0.000	0.000	1.000	1.000

Table S3c. Bootstrap MEA results for Infrastructure

Country	Code	MEAeff	Bias-corrected	Bootstrap Bias	Std.Error	2.5% CI	97.5% CI
Albania	AL	0.754	0.755	-0.001	0.018	0.728	0.780
Algeria	DZ	0.767	0.763	0.004	0.022	0.727	0.793
Argentina	AR	0.800	0.794	0.006	0.022	0.758	0.820
Armenia	AM	1.000	1.000	0.000	0.000	1.000	1.000
Australia	AU	0.851	0.836	0.016	0.028	0.803	0.858
Austria	AT	0.907	0.880	0.027	0.043	0.851	0.910
Azerbaijan	AZ	0.833	0.818	0.015	0.039	0.731	0.858
Bahrain	BH	0.808	0.803	0.006	0.020	0.774	0.831
Bangladesh	BD	0.854	0.842	0.013	0.042	0.765	0.883
Belarus	BY	0.835	0.830	0.005	0.031	0.768	0.865
Belgium	BE	0.934	0.910	0.025	0.037	0.894	0.938
Benin	BJ	0.849	0.827	0.021	0.035	0.794	0.858
Bhutan	BT	0.735	0.732	0.002	0.021	0.698	0.759
Bolivia, Plurinational State of	BO	0.856	0.815	0.041	0.073	0.768	0.875
Bosnia and Herzegovina	BA	0.797	0.782	0.015	0.026	0.756	0.805
Botswana	BW	0.761	0.750	0.010	0.025	0.714	0.783
Brazil	BR	0.816	0.811	0.004	0.019	0.781	0.839
Bulgaria	BG	0.945	0.925	0.021	0.032	0.912	0.948
Burkina Faso	BF	0.832	0.794	0.037	0.058	0.736	0.837
Burundi	BI	0.818	0.811	0.007	0.027	0.769	0.840
Cote d'Ivoire	CI	1.000	1.000	0.000	0.000	1.000	1.000
Cambodia	KH	0.948	0.927	0.021	0.032	0.916	0.952
Cameroon	CM	0.881	0.867	0.014	0.025	0.838	0.893
Canada	CA	0.884	0.868	0.016	0.026	0.844	0.892
Chile	CL	0.842	0.839	0.002	0.017	0.811	0.862
China	CN	1.000	1.000	0.000	0.000	1.000	1.000
Colombia	CO	0.822	0.825	-0.003	0.018	0.794	0.850
Costa Rica	CR	0.880	0.857	0.023	0.048	0.807	0.894
Croatia	HR	0.861	0.850	0.011	0.022	0.820	0.874
Cyprus	CY	0.976	0.963	0.013	0.017	0.962	0.973
Czech Republic	CZ	0.931	0.904	0.026	0.038	0.888	0.932
Denmark	DK	0.928	0.903	0.025	0.036	0.884	0.926
Dominican Republic	DO	0.870	0.853	0.017	0.046	0.791	0.904
Ecuador	EC	0.844	0.816	0.028	0.058	0.748	0.875
Egypt	EG	0.824	0.813	0.011	0.029	0.780	0.849
El Salvador	SV	0.817	0.807	0.010	0.038	0.740	0.847
Estonia	EE	1.000	1.000	0.000	0.000	1.000	1.000
Ethiopia	ET	0.968	0.950	0.018	0.024	0.948	0.969
Finland	FI	0.926	0.900	0.026	0.039	0.881	0.930
France	FR	0.892	0.875	0.017	0.030	0.826	0.899
Georgia	GE	0.890	0.854	0.036	0.057	0.823	0.893
Germany	DE	0.968	0.950	0.018	0.024	0.948	0.965
Ghana	GH	0.845	0.837	0.007	0.022	0.806	0.866
Greece	GR	0.843	0.807	0.036	0.062	0.747	0.855
Guatemala	GT	0.919	0.897	0.022	0.037	0.869	0.934

Guinea	GN	0.868	0.841	0.027	0.060	0.787	0.890
Honduras	HN	0.853	0.842	0.011	0.029	0.804	0.881
Hong Kong (China)	HK	0.861	0.852	0.009	0.021	0.824	0.873
Hungary	HU	1.000	1.000	0.000	0.000	1.000	1.000
Iceland	IS	1.000	1.000	0.000	0.000	1.000	1.000
India	IN	0.906	0.881	0.025	0.041	0.848	0.918
Indonesia	ID	0.896	0.877	0.019	0.041	0.832	0.916
Iran, Islamic Republic of	IR	0.879	0.843	0.036	0.059	0.805	0.888
Ireland	IE	0.997	0.995	0.002	0.002	0.995	0.995
Israel	IL	0.933	0.901	0.032	0.045	0.893	0.935
Italy	IT	0.875	0.848	0.027	0.047	0.799	0.882
Jamaica	JM	0.864	0.856	0.008	0.022	0.825	0.877
Japan	JP	0.872	0.858	0.014	0.029	0.821	0.888
Jordan	JO	0.869	0.833	0.036	0.062	0.789	0.883
Kazakhstan	KZ	0.779	0.772	0.006	0.020	0.744	0.805
Kenya	KE	0.963	0.940	0.023	0.029	0.940	0.940
Korea, Republic of	KR	0.922	0.886	0.037	0.056	0.875	0.943
Kuwait	KW	1.000	1.000	0.000	0.000	1.000	1.000
Kyrgyzstan	KG	0.806	0.772	0.034	0.073	0.687	0.850
Latvia	LV	0.928	0.900	0.028	0.044	0.885	0.938
Lebanon	LB	0.908	0.885	0.023	0.041	0.851	0.916
Lithuania	LT	0.837	0.812	0.025	0.041	0.770	0.844
Luxembourg	LU	1.000	1.000	0.000	0.000	1.000	1.000
Madagascar	MG	0.999	0.998	0.001	0.001	0.998	0.998
Malawi	MW	0.988	0.981	0.007	0.009	0.981	0.984
Malaysia	MY	0.879	0.863	0.015	0.026	0.837	0.888
Mali	ML	1.000	1.000	0.000	0.000	1.000	1.000
Malta	MT	1.000	1.000	0.000	0.000	1.000	1.000
Mauritius	MU	0.858	0.846	0.012	0.026	0.817	0.878
Mexico	MX	0.859	0.851	0.009	0.020	0.823	0.873
Moldova, Republic of	MD	1.000	1.000	0.000	0.000	1.000	1.000
Mongolia	MN	0.936	0.915	0.021	0.036	0.896	0.943
Montenegro	ME	0.864	0.856	0.008	0.022	0.824	0.880
Morocco	MA	0.883	0.820	0.063	0.085	0.811	0.878
Mozambique	MZ	0.965	0.946	0.019	0.026	0.944	0.965
Namibia	NA	0.896	0.842	0.054	0.075	0.832	0.896
Nepal	NP	0.867	0.851	0.015	0.028	0.819	0.878
Netherlands	NL	0.940	0.917	0.024	0.036	0.904	0.941
New Zealand	NZ	0.907	0.868	0.039	0.055	0.850	0.904
Nicaragua	NI	0.821	0.825	-0.004	0.037	0.712	0.864
Niger	NE	0.884	0.861	0.023	0.043	0.813	0.903
Nigeria	NG	0.934	0.901	0.033	0.046	0.893	0.936
Norway	NO	0.857	0.840	0.017	0.036	0.769	0.868
Oman	OM	0.788	0.720	0.068	0.113	0.659	0.800
Pakistan	PK	0.913	0.877	0.036	0.055	0.859	0.920
Panama	PA	0.879	0.869	0.011	0.038	0.806	0.903
Paraguay	PY	0.906	0.870	0.037	0.059	0.849	0.922
Peru	PE	0.816	0.816	0.000	0.022	0.779	0.842

Philippines	PH	0.905	0.859	0.045	0.066	0.846	0.915
Poland	PL	0.872	0.857	0.015	0.027	0.830	0.880
Portugal	PT	0.905	0.862	0.042	0.061	0.846	0.905
Qatar	QA	0.805	0.799	0.006	0.034	0.738	0.834
Romania	RO	0.890	0.860	0.030	0.052	0.823	0.898
Russian Federation	RU	0.865	0.850	0.014	0.031	0.812	0.888
Rwanda	RW	0.784	0.785	0.000	0.015	0.760	0.807
Saudi Arabia	SA	0.830	0.818	0.012	0.029	0.770	0.841
Senegal	SN	0.908	0.877	0.031	0.050	0.852	0.917
Serbia	RS	0.853	0.836	0.017	0.043	0.763	0.877
Singapore	SG	0.857	0.841	0.016	0.031	0.805	0.871
Slovakia	SK	0.900	0.880	0.020	0.038	0.839	0.913
Slovenia	SI	0.914	0.885	0.029	0.048	0.861	0.922
South Africa	ZA	0.870	0.859	0.011	0.022	0.832	0.885
Spain	ES	0.864	0.819	0.045	0.072	0.781	0.876
Sri Lanka	LK	0.895	0.861	0.034	0.061	0.831	0.918
Sweden	SE	0.969	0.952	0.017	0.023	0.951	0.973
Switzerland	CH	1.000	1.000	0.000	0.000	1.000	1.000
Tajikistan	TJ	1.000	1.000	0.000	0.000	1.000	1.000
Tanzania, United Republic of	TZ	1.000	1.000	0.000	0.000	1.000	1.000
Thailand	TH	0.899	0.887	0.012	0.024	0.842	0.912
The Former Yugoslav Republic (FYR) of Macedonia	MK	0.939	0.919	0.020	0.033	0.902	0.944
Togo	TG	0.883	0.845	0.037	0.055	0.811	0.877
Tunisia	TN	0.827	0.808	0.020	0.045	0.722	0.846
Turkey	TR	1.000	1.000	0.000	0.000	1.000	1.000
Uganda	UG	0.815	0.811	0.004	0.021	0.778	0.842
Ukraine	UA	0.978	0.966	0.012	0.016	0.964	0.979
United Arab Emirates	AE	0.766	0.769	-0.003	0.016	0.745	0.790
United Kingdom	GB	0.956	0.931	0.024	0.032	0.928	0.958
United States of America	US	0.938	0.909	0.029	0.042	0.900	0.944
Uruguay	UY	0.836	0.821	0.015	0.044	0.736	0.863
Venezuela, Bolivarian Republic of	VE	1.000	1.000	0.000	0.000	1.000	1.000
Viet Nam	VN	0.957	0.934	0.022	0.031	0.930	0.959
Yemen	YE	0.847	0.783	0.063	0.100	0.753	0.889
Zambia	ZM	1.000	1.000	0.000	0.000	1.000	1.000

Table S3d. Bootstrap MEA results for Market Sophistication

Country	Code	MEAeff	Bias-corrected	Bootstrap Bias	Std.Error	2.5% CI	97.5% CI
Albania	AL	0.746	0.752	-0.006	0.018	0.728	0.779
Algeria	DZ	0.807	0.801	0.006	0.022	0.766	0.830
Argentina	AR	0.790	0.761	0.029	0.051	0.712	0.808
Armenia	AM	1.000	1.000	0.000	0.000	1.000	1.000
Australia	AU	0.798	0.765	0.034	0.056	0.713	0.809
Austria	AT	0.889	0.851	0.038	0.057	0.820	0.896
Azerbaijan	AZ	0.780	0.762	0.018	0.052	0.645	0.832
Bahrain	BH	0.858	0.839	0.018	0.033	0.803	0.876
Bangladesh	BD	0.826	0.811	0.015	0.052	0.719	0.861
Belarus	BY	0.872	0.862	0.010	0.030	0.807	0.897
Belgium	BE	0.940	0.913	0.027	0.037	0.904	0.938
Benin	BJ	0.722	0.690	0.032	0.053	0.648	0.746
Bhutan	BT	0.719	0.701	0.017	0.042	0.655	0.744
Bolivia, Plurinational State of	BO	0.802	0.749	0.053	0.099	0.680	0.834
Bosnia and Herzegovina	BA	0.738	0.724	0.014	0.027	0.692	0.752
Botswana	BW	0.752	0.748	0.003	0.020	0.717	0.778
Brazil	BR	0.821	0.814	0.007	0.024	0.780	0.852
Bulgaria	BG	0.927	0.899	0.028	0.043	0.883	0.937
Burkina Faso	BF	0.794	0.759	0.035	0.057	0.682	0.802
Burundi	BI	0.722	0.712	0.010	0.040	0.652	0.761
Cote d'Ivoire	CI	1.000	1.000	0.000	0.000	1.000	1.000
Cambodia	KH	0.845	0.794	0.051	0.089	0.750	0.879
Cameroon	CM	0.805	0.799	0.006	0.026	0.764	0.839
Canada	CA	0.837	0.821	0.016	0.031	0.785	0.853
Chile	CL	0.833	0.820	0.013	0.032	0.782	0.859
China	CN	1.000	1.000	0.000	0.000	1.000	1.000
Colombia	CO	0.800	0.791	0.009	0.032	0.749	0.831
Costa Rica	CR	0.873	0.833	0.040	0.067	0.795	0.890
Croatia	HR	0.849	0.822	0.027	0.047	0.778	0.865
Cyprus	CY	0.939	0.908	0.031	0.043	0.902	0.942
Czech Republic	CZ	0.937	0.912	0.026	0.037	0.899	0.937
Denmark	DK	0.879	0.851	0.028	0.049	0.805	0.890
Dominican Republic	DO	0.809	0.775	0.035	0.074	0.692	0.861
Ecuador	EC	0.794	0.755	0.039	0.081	0.668	0.837
Egypt	EG	0.829	0.811	0.018	0.038	0.770	0.849
El Salvador	SV	0.764	0.740	0.023	0.061	0.649	0.803
Estonia	EE	1.000	1.000	0.000	0.000	1.000	1.000
Ethiopia	ET	0.969	0.950	0.018	0.024	0.949	0.966
Finland	FI	0.907	0.874	0.033	0.048	0.851	0.906
France	FR	0.870	0.844	0.026	0.044	0.790	0.881
Georgia	GE	0.888	0.850	0.038	0.060	0.819	0.895
Germany	DE	0.962	0.941	0.021	0.028	0.939	0.959
Ghana	GH	0.837	0.832	0.005	0.020	0.804	0.863
Greece	GR	0.808	0.762	0.046	0.078	0.691	0.821
Guatemala	GT	0.789	0.751	0.038	0.074	0.660	0.834

Guinea	GN	0.784	0.735	0.049	0.101	0.651	0.822
Honduras	HN	0.755	0.741	0.015	0.044	0.684	0.811
Hong Kong (China)	HK	0.791	0.772	0.018	0.037	0.733	0.811
Hungary	HU	1.000	1.000	0.000	0.000	1.000	1.000
Iceland	IS	1.000	1.000	0.000	0.000	1.000	1.000
India	IN	0.863	0.844	0.018	0.050	0.778	0.897
Indonesia	ID	0.879	0.861	0.018	0.047	0.805	0.904
Iran, Islamic Republic of	IR	0.887	0.856	0.031	0.056	0.818	0.908
Ireland	IE	0.999	0.998	0.001	0.001	0.998	0.998
Israel	IL	0.940	0.909	0.031	0.042	0.903	0.938
Italy	IT	0.900	0.874	0.026	0.044	0.838	0.910
Jamaica	JM	0.776	0.761	0.015	0.038	0.714	0.804
Japan	JP	0.870	0.857	0.012	0.028	0.818	0.886
Jordan	JO	0.898	0.865	0.032	0.055	0.835	0.918
Kazakhstan	KZ	0.810	0.797	0.013	0.027	0.765	0.830
Kenya	KE	0.942	0.906	0.035	0.045	0.906	0.906
Korea, Republic of	KR	0.956	0.933	0.022	0.031	0.928	0.962
Kuwait	KW	1.000	1.000	0.000	0.000	1.000	1.000
Kyrgyzstan	KG	0.783	0.753	0.030	0.077	0.651	0.828
Latvia	LV	0.912	0.872	0.040	0.057	0.858	0.920
Lebanon	LB	0.855	0.819	0.036	0.065	0.766	0.870
Lithuania	LT	0.819	0.771	0.047	0.075	0.715	0.825
Luxembourg	LU	1.000	1.000	0.000	0.000	1.000	1.000
Madagascar	MG	0.890	0.823	0.067	0.086	0.823	0.823
Malawi	MW	0.964	0.943	0.021	0.027	0.943	0.955
Malaysia	MY	0.848	0.834	0.014	0.028	0.803	0.869
Mali	ML	1.000	1.000	0.000	0.000	1.000	1.000
Malta	MT	1.000	1.000	0.000	0.000	1.000	1.000
Mauritius	MU	0.813	0.799	0.015	0.038	0.756	0.852
Mexico	MX	0.813	0.797	0.017	0.036	0.755	0.837
Moldova, Republic of	MD	1.000	1.000	0.000	0.000	1.000	1.000
Mongolia	MN	0.850	0.805	0.045	0.080	0.757	0.874
Montenegro	ME	0.826	0.802	0.024	0.049	0.751	0.848
Morocco	MA	0.925	0.882	0.042	0.056	0.878	0.910
Mozambique	MZ	0.930	0.894	0.036	0.050	0.887	0.935
Namibia	NA	0.839	0.756	0.083	0.115	0.740	0.839
Nepal	NP	0.846	0.835	0.011	0.030	0.791	0.877
Netherlands	NL	0.898	0.855	0.043	0.063	0.835	0.899
New Zealand	NZ	0.856	0.801	0.054	0.080	0.767	0.857
Nicaragua	NI	0.741	0.748	-0.007	0.053	0.583	0.805
Niger	NE	0.892	0.866	0.026	0.043	0.826	0.899
Nigeria	NG	0.881	0.825	0.056	0.082	0.808	0.891
Norway	NO	0.861	0.823	0.037	0.060	0.775	0.871
Oman	OM	0.804	0.734	0.070	0.108	0.685	0.811
Pakistan	PK	0.884	0.838	0.046	0.072	0.813	0.901
Panama	PA	0.872	0.848	0.024	0.049	0.794	0.897
Paraguay	PY	0.809	0.739	0.070	0.117	0.693	0.845
Peru	PE	0.766	0.760	0.006	0.037	0.704	0.803

Philippines	PH	0.943	0.914	0.028	0.040	0.908	0.945
Poland	PL	0.830	0.798	0.032	0.052	0.752	0.841
Portugal	PT	0.882	0.828	0.054	0.076	0.810	0.883
Qatar	QA	0.825	0.796	0.029	0.060	0.727	0.852
Romania	RO	0.920	0.893	0.026	0.043	0.871	0.929
Russian Federation	RU	0.875	0.858	0.017	0.032	0.819	0.886
Rwanda	RW	0.712	0.718	-0.006	0.022	0.689	0.754
Saudi Arabia	SA	0.792	0.767	0.026	0.051	0.699	0.805
Senegal	SN	0.904	0.866	0.038	0.057	0.844	0.912
Serbia	RS	0.910	0.888	0.023	0.036	0.855	0.913
Singapore	SG	0.856	0.839	0.016	0.032	0.796	0.866
Slovakia	SK	0.917	0.895	0.022	0.040	0.866	0.932
Slovenia	SI	0.915	0.883	0.032	0.050	0.863	0.925
South Africa	ZA	0.791	0.791	0.000	0.019	0.760	0.820
Spain	ES	0.871	0.830	0.041	0.070	0.792	0.898
Sri Lanka	LK	0.904	0.866	0.038	0.058	0.845	0.916
Sweden	SE	0.994	0.990	0.004	0.005	0.990	0.992
Switzerland	CH	1.000	1.000	0.000	0.000	1.000	1.000
Tajikistan	TJ	1.000	1.000	0.000	0.000	1.000	1.000
Tanzania, United Republic of	TZ	1.000	1.000	0.000	0.000	1.000	1.000
Thailand	TH	0.865	0.856	0.009	0.030	0.787	0.895
The Former Yugoslav Republic (FYR) of Macedonia	MK	0.846	0.797	0.049	0.086	0.752	0.869
Togo	TG	0.780	0.740	0.040	0.075	0.646	0.800
Tunisia	TN	0.858	0.817	0.040	0.063	0.771	0.868
Turkey	TR	1.000	1.000	0.000	0.000	1.000	1.000
Uganda	UG	0.831	0.824	0.007	0.026	0.789	0.859
Ukraine	UA	0.939	0.909	0.030	0.044	0.902	0.950
United Arab Emirates	AE	0.756	0.741	0.015	0.036	0.701	0.783
United Kingdom	GB	0.930	0.892	0.038	0.051	0.887	0.933
United States of America	US	0.890	0.846	0.044	0.069	0.823	0.909
Uruguay	UY	0.857	0.818	0.039	0.065	0.770	0.872
Venezuela, Bolivarian Republic of	VE	1.000	1.000	0.000	0.000	1.000	1.000
Viet Nam	VN	0.937	0.905	0.031	0.044	0.898	0.939
Yemen	YE	0.777	0.695	0.082	0.146	0.640	0.843
Zambia	ZM	1.000	1.000	0.000	0.000	1.000	1.000

Table S3e. Bootstrap MEA results for Business Sophistication

Country	Code	MEAeff	Bias-corrected	Bootstrap Bias	Std.Error	2.5% CI	97.5% CI
Albania	AL	0.812	0.785	0.026	0.044	0.756	0.828
Algeria	DZ	0.813	0.782	0.031	0.048	0.752	0.824
Argentina	AR	0.801	0.787	0.014	0.027	0.756	0.815
Armenia	AM	1.000	1.000	0.000	0.000	1.000	1.000
Australia	AU	0.865	0.839	0.026	0.039	0.807	0.866
Austria	AT	0.887	0.855	0.031	0.053	0.818	0.908
Azerbaijan	AZ	0.911	0.884	0.026	0.040	0.856	0.917
Bahrain	BH	0.837	0.810	0.027	0.043	0.781	0.849
Bangladesh	BD	0.872	0.848	0.024	0.046	0.794	0.887
Belarus	BY	0.880	0.851	0.029	0.044	0.814	0.881
Belgium	BE	0.919	0.889	0.030	0.049	0.869	0.952
Benin	BJ	0.705	0.690	0.015	0.028	0.660	0.724
Bhutan	BT	0.745	0.734	0.011	0.022	0.706	0.760
Bolivia, Plurinational State of	BO	0.863	0.819	0.044	0.071	0.779	0.868
Bosnia and Herzegovina	BA	0.759	0.727	0.032	0.048	0.700	0.771
Botswana	BW	0.788	0.756	0.032	0.049	0.728	0.797
Brazil	BR	0.793	0.775	0.017	0.032	0.748	0.816
Bulgaria	BG	0.950	0.929	0.021	0.031	0.920	0.952
Burkina Faso	BF	0.700	0.664	0.036	0.064	0.608	0.719
Burundi	BI	0.717	0.719	-0.002	0.024	0.676	0.750
Cote d'Ivoire	CI	1.000	1.000	0.000	0.000	1.000	1.000
Cambodia	KH	0.858	0.807	0.051	0.082	0.771	0.869
Cameroon	CM	0.817	0.800	0.016	0.029	0.775	0.833
Canada	CA	0.880	0.852	0.027	0.043	0.826	0.895
Chile	CL	0.838	0.822	0.016	0.031	0.793	0.861
China	CN	1.000	1.000	0.000	0.000	1.000	1.000
Colombia	CO	0.849	0.836	0.013	0.027	0.808	0.872
Costa Rica	CR	0.855	0.826	0.029	0.056	0.766	0.864
Croatia	HR	0.864	0.843	0.021	0.035	0.812	0.875
Cyprus	CY	0.965	0.946	0.019	0.025	0.943	0.961
Czech Republic	CZ	0.924	0.894	0.030	0.047	0.877	0.941
Denmark	DK	0.917	0.888	0.030	0.046	0.866	0.935
Dominican Republic	DO	0.864	0.841	0.022	0.047	0.780	0.876
Ecuador	EC	0.896	0.867	0.029	0.046	0.832	0.910
Egypt	EG	0.880	0.847	0.033	0.050	0.816	0.891
El Salvador	SV	0.820	0.809	0.011	0.035	0.737	0.845
Estonia	EE	1.000	1.000	0.000	0.000	1.000	1.000
Ethiopia	ET	0.979	0.967	0.012	0.016	0.966	0.976
Finland	FI	0.891	0.860	0.031	0.050	0.825	0.907
France	FR	0.889	0.862	0.027	0.043	0.821	0.905
Georgia	GE	0.929	0.893	0.035	0.047	0.885	0.921
Germany	DE	0.958	0.935	0.023	0.031	0.932	0.962
Ghana	GH	0.837	0.817	0.020	0.036	0.789	0.858
Greece	GR	0.913	0.881	0.032	0.046	0.860	0.909
Guatemala	GT	0.831	0.803	0.028	0.053	0.727	0.842

Guinea	GN	0.808	0.777	0.032	0.085	0.691	0.844
Honduras	HN	0.774	0.767	0.008	0.024	0.731	0.811
Hong Kong (China)	HK	0.855	0.837	0.018	0.030	0.809	0.865
Hungary	HU	1.000	1.000	0.000	0.000	1.000	1.000
Iceland	IS	1.000	1.000	0.000	0.000	1.000	1.000
India	IN	0.919	0.899	0.020	0.033	0.869	0.926
Indonesia	ID	0.929	0.902	0.027	0.040	0.886	0.939
Iran, Islamic Republic of	IR	0.912	0.873	0.039	0.056	0.858	0.915
Ireland	IE	0.995	0.991	0.003	0.004	0.991	0.991
Israel	IL	0.923	0.886	0.037	0.053	0.875	0.925
Italy	IT	0.905	0.867	0.038	0.055	0.847	0.918
Jamaica	JM	0.819	0.810	0.009	0.021	0.780	0.832
Japan	JP	0.875	0.853	0.022	0.037	0.813	0.888
Jordan	JO	0.923	0.893	0.030	0.045	0.877	0.926
Kazakhstan	KZ	0.819	0.783	0.036	0.054	0.754	0.829
Kenya	KE	0.957	0.931	0.026	0.034	0.931	0.931
Korea, Republic of	KR	0.970	0.956	0.014	0.021	0.952	0.978
Kuwait	KW	1.000	1.000	0.000	0.000	1.000	1.000
Kyrgyzstan	KG	0.876	0.828	0.048	0.071	0.801	0.879
Latvia	LV	0.960	0.940	0.020	0.027	0.935	0.959
Lebanon	LB	0.884	0.858	0.026	0.046	0.813	0.891
Lithuania	LT	0.865	0.836	0.029	0.044	0.794	0.864
Luxembourg	LU	1.000	1.000	0.000	0.000	1.000	1.000
Madagascar	MG	0.980	0.968	0.012	0.016	0.968	0.968
Malawi	MW	0.900	0.841	0.059	0.077	0.838	0.895
Malaysia	MY	0.852	0.829	0.023	0.037	0.803	0.866
Mali	ML	1.000	1.000	0.000	0.000	1.000	1.000
Malta	MT	1.000	1.000	0.000	0.000	1.000	1.000
Mauritius	MU	0.892	0.865	0.027	0.042	0.834	0.900
Mexico	MX	0.864	0.845	0.019	0.032	0.816	0.875
Moldova, Republic of	MD	1.000	1.000	0.000	0.000	1.000	1.000
Mongolia	MN	0.954	0.935	0.019	0.028	0.927	0.956
Montenegro	ME	0.851	0.839	0.012	0.024	0.807	0.862
Morocco	MA	0.973	0.959	0.015	0.020	0.957	0.975
Mozambique	MZ	0.907	0.859	0.047	0.066	0.849	0.917
Namibia	NA	0.982	0.973	0.009	0.013	0.971	0.982
Nepal	NP	0.838	0.823	0.016	0.029	0.794	0.855
Netherlands	NL	0.914	0.876	0.038	0.054	0.862	0.912
New Zealand	NZ	0.932	0.902	0.030	0.042	0.890	0.927
Nicaragua	NI	0.770	0.782	-0.012	0.047	0.629	0.824
Niger	NE	0.819	0.792	0.028	0.056	0.709	0.842
Nigeria	NG	0.955	0.932	0.023	0.032	0.928	0.955
Norway	NO	0.876	0.850	0.026	0.044	0.800	0.887
Oman	OM	0.922	0.889	0.032	0.046	0.874	0.922
Pakistan	PK	0.910	0.873	0.038	0.057	0.855	0.919
Panama	PA	0.905	0.885	0.021	0.037	0.848	0.922
Paraguay	PY	0.925	0.893	0.033	0.047	0.879	0.930
Peru	PE	0.813	0.806	0.007	0.022	0.776	0.836

Philippines	PH	0.959	0.938	0.021	0.029	0.934	0.957
Poland	PL	0.873	0.851	0.023	0.036	0.821	0.880
Portugal	PT	0.948	0.922	0.026	0.035	0.916	0.945
Qatar	QA	0.891	0.871	0.020	0.033	0.832	0.896
Romania	RO	0.928	0.896	0.032	0.045	0.884	0.926
Russian Federation	RU	0.858	0.835	0.023	0.038	0.797	0.872
Rwanda	RW	0.723	0.725	-0.002	0.018	0.698	0.750
Saudi Arabia	SA	0.876	0.852	0.024	0.040	0.807	0.881
Senegal	SN	0.919	0.887	0.032	0.047	0.870	0.920
Serbia	RS	0.907	0.880	0.027	0.042	0.850	0.920
Singapore	SG	0.838	0.816	0.023	0.037	0.784	0.853
Slovakia	SK	0.929	0.905	0.024	0.038	0.885	0.937
Slovenia	SI	0.900	0.865	0.035	0.056	0.839	0.910
South Africa	ZA	0.839	0.819	0.020	0.034	0.793	0.852
Spain	ES	0.911	0.871	0.041	0.057	0.857	0.912
Sri Lanka	LK	0.948	0.926	0.023	0.033	0.917	0.955
Sweden	SE	0.991	0.986	0.005	0.007	0.986	0.991
Switzerland	CH	1.000	1.000	0.000	0.000	1.000	1.000
Tajikistan	TJ	1.000	1.000	0.000	0.000	1.000	1.000
Tanzania, United Republic of	TZ	1.000	1.000	0.000	0.000	1.000	1.000
Thailand	TH	0.882	0.862	0.020	0.036	0.820	0.901
The Former Yugoslav Republic (FYR) of Macedonia	MK	0.900	0.866	0.034	0.054	0.838	0.906
Togo	TG	0.806	0.766	0.039	0.069	0.687	0.828
Tunisia	TN	0.884	0.853	0.031	0.048	0.813	0.890
Turkey	TR	1.000	1.000	0.000	0.000	1.000	1.000
Uganda	UG	0.800	0.789	0.011	0.026	0.761	0.826
Ukraine	UA	0.979	0.968	0.011	0.015	0.966	0.981
United Arab Emirates	AE	0.749	0.745	0.004	0.019	0.720	0.773
United Kingdom	GB	0.967	0.948	0.019	0.024	0.946	0.965
United States of America	US	0.960	0.941	0.020	0.027	0.936	0.963
Uruguay	UY	0.917	0.896	0.022	0.035	0.866	0.921
Venezuela, Bolivarian Republic of	VE	1.000	1.000	0.000	0.000	1.000	1.000
Viet Nam	VN	0.963	0.943	0.020	0.027	0.940	0.962
Yemen	YE	0.920	0.882	0.038	0.054	0.871	0.920
Zambia	ZM	1.000	1.000	0.000	0.000	1.000	1.000

Table S3f. Bootstrap MEA results for Knowledge & Technology Outputs

Country	Code	MEAeff	Bias-corrected	Bootstrap Bias	Std.Error	2.5% CI	97.5% CI
Albania	AL	0.799	0.769	0.029	0.043	0.737	0.806
Algeria	DZ	0.827	0.808	0.019	0.034	0.772	0.843
Argentina	AR	0.735	0.718	0.017	0.037	0.671	0.761
Armenia	AM	1.000	1.000	0.000	0.000	1.000	1.000
Australia	AU	0.801	0.774	0.027	0.043	0.738	0.815
Austria	AT	0.897	0.869	0.029	0.046	0.835	0.908
Azerbaijan	AZ	0.851	0.809	0.043	0.064	0.760	0.851
Bahrain	BH	0.862	0.845	0.016	0.029	0.811	0.870
Bangladesh	BD	0.881	0.849	0.033	0.054	0.808	0.899
Belarus	BY	0.909	0.892	0.017	0.028	0.858	0.914
Belgium	BE	0.954	0.934	0.019	0.028	0.925	0.953
Benin	BJ	0.673	0.641	0.032	0.051	0.587	0.678
Bhutan	BT	0.113	0.109	0.004	0.009	0.096	0.118
Bolivia, Plurinational State of	BO	0.870	0.816	0.054	0.080	0.790	0.890
Bosnia and Herzegovina	BA	0.736	0.716	0.020	0.034	0.675	0.746
Botswana	BW	0.782	0.758	0.024	0.040	0.724	0.795
Brazil	BR	0.810	0.789	0.021	0.035	0.746	0.819
Bulgaria	BG	0.955	0.935	0.020	0.028	0.927	0.952
Burkina Faso	BF	0.816	0.760	0.056	0.086	0.703	0.829
Burundi	BI	0.525	0.484	0.041	0.068	0.417	0.541
Cote d'Ivoire	CI	1.000	1.000	0.000	0.000	1.000	1.000
Cambodia	KH	0.924	0.890	0.034	0.048	0.878	0.923
Cameroon	CM	0.825	0.794	0.031	0.047	0.754	0.834
Canada	CA	0.884	0.865	0.019	0.032	0.833	0.896
Chile	CL	0.824	0.806	0.018	0.031	0.775	0.836
China	CN	1.000	1.000	0.000	0.000	1.000	1.000
Colombia	CO	0.817	0.803	0.014	0.025	0.776	0.829
Costa Rica	CR	0.858	0.817	0.041	0.065	0.770	0.858
Croatia	HR	0.847	0.831	0.016	0.029	0.793	0.856
Cyprus	CY	0.975	0.961	0.014	0.019	0.960	0.974
Czech Republic	CZ	0.951	0.932	0.020	0.028	0.921	0.953
Denmark	DK	0.924	0.899	0.025	0.038	0.877	0.931
Dominican Republic	DO	0.841	0.799	0.042	0.068	0.743	0.844
Ecuador	EC	0.736	0.691	0.046	0.089	0.575	0.747
Egypt	EG	0.889	0.867	0.022	0.036	0.840	0.904
El Salvador	SV	0.577	0.536	0.041	0.073	0.446	0.594
Estonia	EE	1.000	1.000	0.000	0.000	1.000	1.000
Ethiopia	ET	0.975	0.960	0.015	0.019	0.960	0.971
Finland	FI	0.935	0.913	0.022	0.034	0.894	0.938
France	FR	0.892	0.871	0.021	0.037	0.825	0.903
Georgia	GE	0.943	0.915	0.028	0.038	0.908	0.941
Germany	DE	0.973	0.958	0.015	0.020	0.957	0.974
Ghana	GH	0.863	0.851	0.011	0.022	0.820	0.873
Greece	GR	0.836	0.781	0.055	0.082	0.736	0.840
Guatemala	GT	0.844	0.794	0.050	0.072	0.748	0.842

Guinea	GN	0.697	0.603	0.094	0.147	0.511	0.697
Honduras	HN	0.712	0.676	0.036	0.053	0.636	0.717
Hong Kong (China)	HK	0.807	0.793	0.014	0.027	0.759	0.820
Hungary	HU	1.000	1.000	0.000	0.000	1.000	1.000
Iceland	IS	1.000	1.000	0.000	0.000	1.000	1.000
India	IN	0.947	0.930	0.017	0.026	0.914	0.949
Indonesia	ID	0.957	0.942	0.016	0.023	0.931	0.960
Iran, Islamic Republic of	IR	0.934	0.907	0.027	0.040	0.894	0.941
Ireland	IE	0.999	0.999	0.001	0.001	0.999	0.999
Israel	IL	0.953	0.929	0.025	0.033	0.925	0.952
Italy	IT	0.934	0.910	0.024	0.035	0.894	0.941
Jamaica	JM	0.724	0.696	0.028	0.043	0.659	0.736
Japan	JP	0.903	0.886	0.017	0.031	0.850	0.914
Jordan	JO	0.921	0.892	0.030	0.046	0.873	0.929
Kazakhstan	KZ	0.829	0.806	0.023	0.039	0.772	0.843
Kenya	KE	0.991	0.985	0.006	0.007	0.985	0.985
Korea, Republic of	KR	0.981	0.971	0.010	0.014	0.969	0.981
Kuwait	KW	1.000	1.000	0.000	0.000	1.000	1.000
Kyrgyzstan	KG	0.900	0.863	0.037	0.054	0.839	0.900
Latvia	LV	0.943	0.916	0.027	0.038	0.907	0.948
Lebanon	LB	0.844	0.809	0.035	0.059	0.749	0.843
Lithuania	LT	0.781	0.748	0.033	0.053	0.696	0.792
Luxembourg	LU	1.000	1.000	0.000	0.000	1.000	1.000
Madagascar	MG	0.992	0.987	0.005	0.006	0.987	0.987
Malawi	MW	0.983	0.972	0.010	0.013	0.972	0.978
Malaysia	MY	0.869	0.854	0.016	0.028	0.816	0.879
Mali	ML	1.000	1.000	0.000	0.000	1.000	1.000
Malta	MT	1.000	1.000	0.000	0.000	1.000	1.000
Mauritius	MU	0.863	0.831	0.032	0.048	0.797	0.865
Mexico	MX	0.832	0.816	0.016	0.030	0.789	0.849
Moldova, Republic of	MD	1.000	1.000	0.000	0.000	1.000	1.000
Mongolia	MN	0.892	0.846	0.046	0.065	0.826	0.893
Montenegro	ME	0.784	0.771	0.013	0.027	0.731	0.797
Morocco	MA	0.948	0.919	0.028	0.038	0.916	0.949
Mozambique	MZ	0.976	0.962	0.014	0.018	0.961	0.977
Namibia	NA	0.632	0.439	0.193	0.263	0.407	0.609
Nepal	NP	0.848	0.810	0.039	0.060	0.762	0.860
Netherlands	NL	0.908	0.868	0.040	0.057	0.852	0.906
New Zealand	NZ	0.878	0.828	0.051	0.075	0.804	0.894
Nicaragua	NI	0.665	0.601	0.063	0.103	0.460	0.658
Niger	NE	0.914	0.889	0.025	0.038	0.861	0.914
Nigeria	NG	0.979	0.968	0.011	0.015	0.966	0.979
Norway	NO	0.859	0.835	0.024	0.043	0.772	0.867
Oman	OM	0.836	0.770	0.066	0.096	0.736	0.833
Pakistan	PK	0.959	0.940	0.019	0.027	0.934	0.960
Panama	PA	0.910	0.885	0.025	0.040	0.855	0.918
Paraguay	PY	0.671	0.547	0.123	0.196	0.469	0.685
Peru	PE	0.682	0.668	0.014	0.028	0.633	0.699

Philippines	PH	0.977	0.964	0.013	0.017	0.963	0.976
Poland	PL	0.832	0.807	0.025	0.040	0.770	0.845
Portugal	PT	0.879	0.823	0.056	0.081	0.805	0.898
Qatar	QA	0.766	0.736	0.031	0.052	0.683	0.775
Romania	RO	0.949	0.925	0.023	0.032	0.917	0.946
Russian Federation	RU	0.895	0.878	0.017	0.034	0.836	0.910
Rwanda	RW	0.628	0.597	0.031	0.050	0.549	0.642
Saudi Arabia	SA	0.785	0.762	0.023	0.042	0.711	0.805
Senegal	SN	0.921	0.889	0.032	0.049	0.873	0.935
Serbia	RS	0.933	0.917	0.016	0.027	0.892	0.939
Singapore	SG	0.869	0.847	0.022	0.040	0.802	0.880
Slovakia	SK	0.934	0.910	0.024	0.035	0.894	0.935
Slovenia	SI	0.919	0.887	0.031	0.047	0.869	0.920
South Africa	ZA	0.840	0.825	0.015	0.027	0.788	0.851
Spain	ES	0.930	0.901	0.030	0.043	0.888	0.937
Sri Lanka	LK	0.973	0.960	0.013	0.018	0.957	0.974
Sweden	SE	0.997	0.995	0.002	0.002	0.995	0.996
Switzerland	CH	1.000	1.000	0.000	0.000	1.000	1.000
Tajikistan	TJ	1.000	1.000	0.000	0.000	1.000	1.000
Tanzania, United Republic of	TZ	1.000	1.000	0.000	0.000	1.000	1.000
Thailand	TH	0.919	0.900	0.019	0.029	0.869	0.923
The Former Yugoslav Republic (FYR) of Macedonia	MK	0.816	0.752	0.064	0.098	0.704	0.818
Togo	TG	0.882	0.839	0.043	0.063	0.809	0.884
Tunisia	TN	0.866	0.839	0.027	0.049	0.784	0.883
Turkey	TR	1.000	1.000	0.000	0.000	1.000	1.000
Uganda	UG	0.810	0.776	0.033	0.054	0.726	0.819
Ukraine	UA	0.984	0.977	0.008	0.011	0.975	0.987
United Arab Emirates	AE	0.650	0.638	0.012	0.025	0.596	0.662
United Kingdom	GB	0.970	0.954	0.017	0.022	0.952	0.970
United States of America	US	0.975	0.963	0.012	0.017	0.960	0.978
Uruguay	UY	0.857	0.821	0.035	0.058	0.769	0.870
Venezuela, Bolivarian Republic of	VE	1.000	1.000	0.000	0.000	1.000	1.000
Viet Nam	VN	0.980	0.970	0.010	0.014	0.969	0.980
Yemen	YE	0.941	0.913	0.028	0.039	0.905	0.941
Zambia	ZM	1.000	1.000	0.000	0.000	1.000	1.000

Table S3g. Bootstrap MEA results for Creative Outputs

Country	Code	MEAeff	Bias-corrected	Bootstrap Bias	Std.Error	2.5% CI	97.5% CI
Albania	AL	0.697	0.684	0.013	0.028	0.648	0.715
Algeria	DZ	0.674	0.656	0.018	0.036	0.616	0.691
Argentina	AR	0.823	0.792	0.031	0.049	0.748	0.824
Armenia	AM	1.000	1.000	0.000	0.000	1.000	1.000
Australia	AU	0.857	0.825	0.032	0.050	0.785	0.861
Austria	AT	0.874	0.829	0.045	0.069	0.796	0.885
Azerbaijan	AZ	0.916	0.894	0.022	0.035	0.865	0.919
Bahrain	BH	0.792	0.761	0.031	0.054	0.706	0.805
Bangladesh	BD	0.813	0.773	0.040	0.074	0.699	0.830
Belarus	BY	0.430	0.414	0.016	0.055	0.360	0.462
Belgium	BE	0.909	0.871	0.038	0.054	0.853	0.913
Benin	BJ	0.803	0.771	0.032	0.053	0.725	0.807
Bhutan	BT	0.672	0.639	0.033	0.055	0.578	0.681
Bolivia, Plurinational State of	BO	0.927	0.896	0.031	0.043	0.882	0.925
Bosnia and Herzegovina	BA	0.690	0.654	0.036	0.055	0.614	0.695
Botswana	BW	0.631	0.615	0.016	0.031	0.581	0.647
Brazil	BR	0.765	0.747	0.018	0.038	0.704	0.786
Bulgaria	BG	0.960	0.942	0.018	0.025	0.935	0.959
Burkina Faso	BF	0.094	0.065	0.029	0.109	0.027	0.097
Burundi	BI	0.767	0.733	0.033	0.057	0.676	0.780
Cote d'Ivoire	CI	1.000	1.000	0.000	0.000	1.000	1.000
Cambodia	KH	0.915	0.876	0.039	0.054	0.863	0.915
Cameroon	CM	0.824	0.805	0.020	0.041	0.756	0.841
Canada	CA	0.856	0.828	0.028	0.045	0.789	0.863
Chile	CL	0.811	0.784	0.026	0.045	0.730	0.821
China	CN	1.000	1.000	0.000	0.000	1.000	1.000
Colombia	CO	0.842	0.821	0.021	0.037	0.778	0.851
Costa Rica	CR	0.885	0.849	0.036	0.059	0.815	0.887
Croatia	HR	0.842	0.810	0.032	0.053	0.762	0.854
Cyprus	CY	0.961	0.938	0.022	0.029	0.936	0.953
Czech Republic	CZ	0.923	0.891	0.032	0.046	0.876	0.926
Denmark	DK	0.907	0.871	0.036	0.051	0.851	0.905
Dominican Republic	DO	0.905	0.875	0.030	0.046	0.848	0.906
Ecuador	EC	0.920	0.891	0.028	0.043	0.870	0.919
Egypt	EG	0.877	0.850	0.028	0.045	0.811	0.883
El Salvador	SV	0.828	0.789	0.039	0.063	0.726	0.832
Estonia	EE	1.000	1.000	0.000	0.000	1.000	1.000
Ethiopia	ET	0.983	0.973	0.010	0.013	0.973	0.982
Finland	FI	0.869	0.822	0.047	0.068	0.789	0.869
France	FR	0.910	0.886	0.023	0.036	0.854	0.913
Georgia	GE	0.895	0.850	0.044	0.063	0.830	0.897
Germany	DE	0.973	0.958	0.015	0.020	0.957	0.970
Ghana	GH	0.783	0.763	0.020	0.038	0.720	0.799
Greece	GR	0.916	0.887	0.029	0.043	0.864	0.911
Guatemala	GT	0.902	0.869	0.033	0.049	0.842	0.902

Guinea	GN	0.844	0.796	0.048	0.080	0.749	0.866
Honduras	HN	0.850	0.822	0.027	0.048	0.779	0.863
Hong Kong (China)	HK	0.842	0.814	0.028	0.046	0.775	0.854
Hungary	HU	1.000	1.000	0.000	0.000	1.000	1.000
Iceland	IS	1.000	1.000	0.000	0.000	1.000	1.000
India	IN	0.807	0.767	0.040	0.071	0.688	0.819
Indonesia	ID	0.941	0.920	0.022	0.031	0.905	0.942
Iran, Islamic Republic of	IR	0.910	0.877	0.033	0.050	0.855	0.915
Ireland	IE	0.988	0.980	0.008	0.010	0.980	0.980
Israel	IL	0.948	0.919	0.029	0.038	0.916	0.948
Italy	IT	0.901	0.866	0.035	0.051	0.840	0.903
Jamaica	JM	0.818	0.794	0.024	0.044	0.743	0.827
Japan	JP	0.790	0.767	0.023	0.042	0.721	0.804
Jordan	JO	0.920	0.890	0.031	0.045	0.872	0.923
Kazakhstan	KZ	0.756	0.732	0.024	0.041	0.689	0.767
Kenya	KE	0.995	0.992	0.003	0.004	0.992	0.992
Korea, Republic of	KR	0.947	0.920	0.028	0.038	0.915	0.947
Kuwait	KW	1.000	1.000	0.000	0.000	1.000	1.000
Kyrgyzstan	KG	0.825	0.774	0.051	0.083	0.718	0.836
Latvia	LV	0.962	0.943	0.019	0.026	0.938	0.963
Lebanon	LB	0.915	0.888	0.027	0.044	0.862	0.921
Lithuania	LT	0.853	0.809	0.044	0.065	0.767	0.857
Luxembourg	LU	1.000	1.000	0.000	0.000	1.000	1.000
Madagascar	MG	0.999	0.998	0.001	0.001	0.998	0.998
Malawi	MW	0.979	0.967	0.012	0.016	0.967	0.972
Malaysia	MY	0.837	0.813	0.024	0.041	0.773	0.848
Mali	ML	1.000	1.000	0.000	0.000	1.000	1.000
Malta	MT	1.000	1.000	0.000	0.000	1.000	1.000
Mauritius	MU	0.889	0.867	0.023	0.036	0.830	0.896
Mexico	MX	0.845	0.820	0.025	0.042	0.782	0.857
Moldova, Republic of	MD	1.000	1.000	0.000	0.000	1.000	1.000
Mongolia	MN	0.959	0.942	0.017	0.025	0.934	0.960
Montenegro	ME	0.828	0.794	0.034	0.056	0.746	0.839
Morocco	MA	0.976	0.963	0.013	0.017	0.962	0.978
Mozambique	MZ	0.911	0.862	0.049	0.065	0.857	0.899
Namibia	NA	0.985	0.977	0.008	0.011	0.977	0.985
Nepal	NP	0.785	0.753	0.032	0.053	0.693	0.797
Netherlands	NL	0.938	0.913	0.025	0.038	0.901	0.941
New Zealand	NZ	0.933	0.904	0.029	0.041	0.891	0.925
Nicaragua	NI	0.758	0.703	0.055	0.098	0.610	0.785
Niger	NE	0.040	-0.024	0.064	0.240	-0.548	0.043
Nigeria	NG	0.967	0.949	0.018	0.024	0.947	0.966
Norway	NO	0.857	0.819	0.038	0.063	0.770	0.868
Oman	OM	0.926	0.895	0.031	0.043	0.881	0.926
Pakistan	PK	0.912	0.869	0.043	0.059	0.858	0.912
Panama	PA	0.906	0.882	0.024	0.039	0.848	0.910
Paraguay	PY	0.936	0.908	0.028	0.041	0.897	0.937
Peru	PE	0.808	0.786	0.023	0.040	0.738	0.815

Philippines	PH	0.901	0.851	0.051	0.069	0.841	0.898
Poland	PL	0.857	0.827	0.030	0.048	0.787	0.865
Portugal	PT	0.950	0.927	0.024	0.033	0.920	0.948
Qatar	QA	0.891	0.866	0.025	0.040	0.828	0.900
Romania	RO	0.909	0.873	0.036	0.053	0.854	0.911
Russian Federation	RU	0.813	0.786	0.027	0.046	0.730	0.819
Rwanda	RW	0.660	0.637	0.023	0.042	0.588	0.676
Saudi Arabia	SA	0.883	0.856	0.028	0.045	0.814	0.889
Senegal	SN	0.865	0.811	0.054	0.080	0.782	0.870
Serbia	RS	0.808	0.758	0.051	0.079	0.691	0.816
Singapore	SG	0.755	0.729	0.027	0.045	0.677	0.764
Slovakia	SK	0.920	0.893	0.028	0.041	0.871	0.922
Slovenia	SI	0.891	0.853	0.038	0.064	0.825	0.906
South Africa	ZA	0.801	0.779	0.021	0.040	0.736	0.818
Spain	ES	0.912	0.877	0.035	0.051	0.858	0.916
Sri Lanka	LK	0.960	0.941	0.019	0.026	0.936	0.960
Sweden	SE	0.962	0.940	0.022	0.029	0.938	0.964
Switzerland	CH	1.000	1.000	0.000	0.000	1.000	1.000
Tajikistan	TJ	1.000	1.000	0.000	0.000	1.000	1.000
Tanzania, United Republic of	TZ	1.000	1.000	0.000	0.000	1.000	1.000
Thailand	TH	0.898	0.875	0.023	0.037	0.837	0.908
The Former Yugoslav Republic (FYR) of Macedonia	MK	0.929	0.903	0.026	0.041	0.886	0.935
Togo	TG	0.319	0.231	0.087	0.198	-0.099	0.328
Tunisia	TN	0.871	0.833	0.038	0.059	0.792	0.880
Turkey	TR	1.000	1.000	0.000	0.000	1.000	1.000
Uganda	UG	0.750	0.724	0.026	0.049	0.662	0.765
Ukraine	UA	0.970	0.954	0.016	0.022	0.951	0.971
United Arab Emirates	AE	0.668	0.636	0.032	0.058	0.574	0.681
United Kingdom	GB	0.981	0.971	0.011	0.014	0.970	0.979
United States of America	US	0.940	0.910	0.030	0.041	0.903	0.942
Uruguay	UY	0.916	0.891	0.025	0.040	0.864	0.923
Venezuela, Bolivarian Republic of	VE	1.000	1.000	0.000	0.000	1.000	1.000
Viet Nam	VN	0.966	0.948	0.019	0.025	0.946	0.960
Yemen	YE	0.559	0.386	0.174	0.281	0.289	0.602
Zambia	ZM	1.000	1.000	0.000	0.000	1.000	1.000

Table S4. PLS estimation results

The table presents analytical results for the PLS regression model, applied on the set of innovation inputs and MEA innovation outputs, conditioned on the peers for each country. Columns 2 to 6 and 9 to 13 present the estimated coefficients β_j with a subscript for each input, namely *Institutions* (j=1), *Human Capital & Research* (j=2), *Infrastructure* (j=3), *Market Sophistication* (j=4) and *Business Sophistication* (j=5). Columns Fit_1 and Fit_2 present the fitted values for *Knowledge & Technology* and *Creative Outputs*, respectively. Columns *Res(1)* and *Res(2)* report the residual differences of the estimated model, defined as the difference between the (observed) optimal innovation outputs and the estimated ones. Income groups follow the United Nations 2016 classification.

	(β_1)	(β_2)	(β_3)	(β_4)	(β_5)	Fit_1	Res(1)	(β_1)	(β_2)	(β_3)	(β_4)	(β_5)	Fit_2	Res(2)
Central and Southern Asia														
Low														
Nepal	0.14	0.30	0.20	0.13	0.11	19.32	1.44	0.20	0.40	0.27	0.17	0.15	19.76	0.99
Lower-Middle														
Bangladesh	0.14	0.28	0.21	0.13	0.10	18.59	-0.10	0.19	0.38	0.28	0.17	0.14	18.79	-0.22
Bhutan	0.18	0.34	0.23	0.16	0.18	29.71	-12.09	0.18	0.34	0.23	0.16	0.18	33.88	-0.24
India	0.14	0.30	0.20	0.14	0.12	27.55	5.19	0.17	0.37	0.25	0.17	0.15	32.35	-4.45
Kyrgyzstan	0.15	0.30	0.15	0.09	0.17	24.08	-3.85	0.14	0.27	0.13	0.08	0.15	28.94	-8.22
Pakistan	0.14	0.30	0.20	0.13	0.11	17.56	2.88	0.19	0.40	0.27	0.17	0.15	17.59	-0.16
Sri Lanka	0.14	0.29	0.20	0.13	0.10	22.49	0.53	0.20	0.40	0.28	0.18	0.14	24.32	1.92
Tajikistan	0.13	0.24	0.11	0.06	0.10	23.14	3.86	0.13	0.24	0.11	0.06	0.11	28.21	-3.71
Upper-Middle														
Iran, Islamic Republic of	0.13	0.24	0.11	0.07	0.10	26.27	-0.58	0.13	0.25	0.12	0.07	0.11	31.91	-2.58
Kazakhstan	0.25	0.29	0.20	0.15	0.15	27.94	-2.37	0.22	0.25	0.18	0.13	0.13	33.27	-4.95
Europe														
Lower-Middle														
Moldova, Republic of	0.26	0.27	0.19	0.13	0.18	26.95	7.95	0.23	0.25	0.17	0.12	0.16	32.42	7.18
Ukraine	0.25	0.28	0.18	0.16	0.20	27.03	7.61	0.23	0.26	0.16	0.14	0.18	32.42	-0.46
Upper-Middle														
Albania	0.15	0.28	0.14	0.08	0.14	25.31	-3.78	0.14	0.26	0.13	0.07	0.13	30.91	-8.97
Belarus	0.14	0.31	0.22	0.16	0.14	30.35	0.56	0.15	0.34	0.24	0.17	0.15	35.76	-13.66

Bosnia and Herzegovina	0.14	0.28	0.19	0.12	0.09	28.14	-3.94	0.18	0.37	0.26	0.16	0.12	33.47	-5.05
Bulgaria	0.25	0.28	0.19	0.16	0.20	30.73	2.88	0.21	0.24	0.16	0.13	0.17	36.11	8.68
Montenegro	0.16	0.30	0.15	0.09	0.18	32.08	-2.23	0.14	0.27	0.14	0.08	0.16	37.18	3.65
Romania	0.14	0.28	0.20	0.14	0.10	28.88	3.80	0.19	0.38	0.27	0.19	0.14	34.72	1.13
Russian Federation	0.16	0.32	0.20	0.14	0.14	34.59	1.04	0.20	0.40	0.25	0.17	0.17	41.74	-6.44
Serbia	0.14	0.27	0.13	0.08	0.14	27.91	1.79	0.13	0.26	0.13	0.07	0.13	33.76	-2.20
The Former Yugoslav Republic (FYR) of Macedonia	0.14	0.29	0.22	0.15	0.12	27.95	-1.11	0.16	0.33	0.25	0.17	0.13	32.61	5.17
High														
Austria	0.15	0.32	0.20	0.16	0.16	45.27	-1.37	0.18	0.38	0.24	0.19	0.19	54.40	2.26
Belgium	0.16	0.33	0.21	0.15	0.16	43.86	2.29	0.19	0.39	0.25	0.18	0.19	51.59	0.66
Croatia	0.15	0.31	0.20	0.14	0.12	31.71	-0.41	0.20	0.40	0.25	0.18	0.16	37.88	2.37
Czech Republic	0.15	0.32	0.20	0.16	0.14	38.59	6.40	0.18	0.39	0.25	0.20	0.17	46.94	3.10
Denmark	0.16	0.33	0.21	0.15	0.16	49.33	0.90	0.18	0.38	0.24	0.18	0.18	59.84	-1.10
Estonia	0.16	0.33	0.21	0.14	0.15	37.63	6.27	0.20	0.39	0.25	0.17	0.18	44.41	10.29
Finland	0.13	0.28	0.14	0.08	0.14	44.22	11.53	0.12	0.26	0.12	0.07	0.13	50.70	7.53
France	0.16	0.33	0.21	0.16	0.16	46.35	-0.03	0.18	0.38	0.24	0.19	0.18	56.53	-1.77
Germany	0.15	0.32	0.21	0.18	0.17	46.12	6.89	0.18	0.37	0.24	0.20	0.20	54.68	3.17
Greece	0.15	0.32	0.21	0.14	0.13	36.24	-6.46	0.19	0.40	0.26	0.17	0.17	44.31	-5.76
Hungary	0.16	0.33	0.21	0.14	0.15	34.72	9.68	0.20	0.40	0.25	0.17	0.18	40.87	-4.37
Iceland	0.13	0.28	0.13	0.08	0.14	36.43	4.77	0.12	0.25	0.12	0.07	0.12	42.41	27.09
Ireland	0.15	0.30	0.15	0.09	0.17	43.03	14.93	0.14	0.28	0.14	0.08	0.17	50.61	3.46
Italy	0.15	0.32	0.20	0.14	0.13	38.14	3.30	0.19	0.40	0.25	0.17	0.17	47.12	-0.73
Latvia	0.14	0.31	0.22	0.16	0.14	32.50	1.03	0.15	0.33	0.23	0.17	0.15	37.92	10.11
Lithuania	0.15	0.30	0.22	0.16	0.14	36.66	-3.75	0.18	0.36	0.26	0.20	0.17	44.06	1.65
Luxembourg	0.15	0.30	0.15	0.09	0.17	39.27	9.43	0.14	0.28	0.14	0.09	0.16	45.66	20.74
Malta	0.15	0.31	0.15	0.09	0.18	36.12	2.18	0.13	0.28	0.13	0.08	0.16	41.74	19.66
Netherlands	0.15	0.30	0.15	0.09	0.17	43.05	5.49	0.13	0.26	0.13	0.08	0.15	48.00	17.01
Norway	0.16	0.34	0.21	0.16	0.16	45.42	-3.25	0.18	0.38	0.24	0.18	0.18	53.26	2.62
Poland	0.14	0.31	0.22	0.16	0.14	33.26	-0.56	0.15	0.33	0.23	0.17	0.15	38.86	3.48
Portugal	0.15	0.32	0.20	0.14	0.14	37.57	-0.70	0.19	0.40	0.25	0.17	0.17	45.83	3.95
Slovakia	0.14	0.29	0.19	0.12	0.10	31.34	3.23	0.19	0.40	0.26	0.16	0.14	37.95	4.00
Slovenia	0.25	0.31	0.20	0.21	0.25	39.36	-2.45	0.21	0.26	0.17	0.18	0.21	44.83	4.54
Spain	0.15	0.31	0.22	0.17	0.15	40.39	1.10	0.18	0.35	0.25	0.20	0.17	48.97	-1.15
Sweden	0.17	0.33	0.18	0.18	0.22	52.14	11.96	0.16	0.30	0.16	0.16	0.20	59.26	-3.73
Switzerland	0.14	0.29	0.14	0.08	0.16	45.39	21.61	0.13	0.27	0.13	0.08	0.15	52.23	9.17

United Kingdom	0.15	0.32	0.22	0.16	0.14	48.20	3.53	0.18	0.39	0.26	0.19	0.17	61.68	2.02
Latin America and the Caribbean														
Lower-Middle														
Bolivia, State of	0.20	0.28	0.21	0.16	0.11	21.66	-1.42	0.22	0.32	0.24	0.18	0.12	24.83	-3.15
El Salvador	0.14	0.27	0.19	0.12	0.09	22.84	-4.30	0.19	0.37	0.26	0.16	0.12	25.19	3.44
Guatemala	0.14	0.27	0.19	0.12	0.08	21.24	-0.03	0.20	0.39	0.28	0.18	0.12	22.20	4.40
Honduras	0.13	0.26	0.12	0.06	0.12	23.65	-3.41	0.13	0.25	0.12	0.06	0.12	28.61	-1.89
Nicaragua	0.14	0.25	0.12	0.07	0.13	20.12	-3.87	0.14	0.25	0.12	0.07	0.13	24.37	-3.40
Upper-Middle														
Argentina	0.13	0.30	0.20	0.14	0.11	28.13	-3.66	0.16	0.37	0.25	0.16	0.14	32.71	-1.99
Brazil	0.25	0.28	0.20	0.17	0.23	29.87	-0.60	0.22	0.25	0.17	0.15	0.20	35.39	-4.53
Colombia	0.25	0.27	0.19	0.14	0.17	28.47	-2.52	0.23	0.25	0.17	0.13	0.16	33.96	-0.83
Costa Rica	0.13	0.25	0.12	0.07	0.12	29.50	1.75	0.13	0.25	0.12	0.07	0.12	35.70	6.11
Dominican Republic	0.18	0.34	0.23	0.16	0.18	23.27	-0.55	0.18	0.34	0.23	0.16	0.18	26.70	3.67
Ecuador	0.14	0.28	0.19	0.13	0.10	23.18	-5.26	0.20	0.40	0.28	0.18	0.14	25.03	4.77
Jamaica	0.14	0.26	0.12	0.06	0.12	24.93	-2.40	0.14	0.26	0.12	0.06	0.12	30.26	-1.39
Mexico	0.13	0.29	0.20	0.15	0.12	29.36	-1.37	0.15	0.35	0.24	0.18	0.14	33.94	1.45
Panama	0.15	0.29	0.14	0.08	0.16	25.76	0.84	0.14	0.27	0.13	0.07	0.15	31.11	1.13
Paraguay	0.15	0.28	0.19	0.12	0.09	23.80	-6.21	0.21	0.40	0.28	0.18	0.13	25.96	7.68
Peru	0.26	0.26	0.19	0.16	0.18	28.58	-4.53	0.23	0.23	0.17	0.14	0.16	33.90	-0.26
Venezuela, Rep. of	0.17	0.30	0.19	0.12	0.17	22.29	-11.19	0.16	0.28	0.18	0.11	0.16	27.03	-9.93
High														
Chile	0.14	0.28	0.14	0.08	0.14	30.90	0.64	0.14	0.27	0.13	0.07	0.14	37.20	1.28
Uruguay	0.14	0.30	0.21	0.16	0.13	28.05	-3.19	0.17	0.37	0.26	0.19	0.16	32.49	1.47
Northern America														
High														
Canada	0.25	0.32	0.19	0.19	0.23	48.67	-2.39	0.21	0.27	0.16	0.16	0.20	53.02	2.01
United States of America	0.15	0.32	0.19	0.17	0.17	50.32	7.63	0.16	0.35	0.21	0.19	0.19	58.16	-3.26
Northern Africa and Western Asia														
Lower-Middle														
Armenia	0.14	0.28	0.19	0.12	0.09	23.60	4.60	0.20	0.40	0.28	0.16	0.12	25.90	9.70
Egypt	0.13	0.30	0.20	0.13	0.11	23.11	-2.30	0.16	0.37	0.25	0.16	0.13	25.77	-0.92

Morocco	0.23	0.30	0.20	0.18	0.16	25.98	-1.82	0.23	0.29	0.19	0.17	0.16	30.47	-1.58
Tunisia	0.14	0.30	0.21	0.14	0.12	27.31	-4.34	0.18	0.37	0.27	0.18	0.15	31.70	-1.73
Yemen	0.18	0.34	0.23	0.16	0.18	12.57	-1.31	0.18	0.34	0.23	0.16	0.18	14.43	-6.92
Upper-Middle														
Algeria	0.14	0.30	0.20	0.12	0.11	23.94	-2.54	0.19	0.40	0.27	0.16	0.15	26.22	-4.56
Azerbaijan	0.13	0.26	0.12	0.07	0.12	24.24	-3.57	0.13	0.26	0.12	0.07	0.12	29.45	-3.15
Georgia	0.15	0.29	0.14	0.08	0.16	25.80	2.62	0.14	0.27	0.13	0.07	0.15	31.34	-1.60
Jordan	0.24	0.29	0.20	0.16	0.12	23.59	-0.03	0.24	0.29	0.20	0.16	0.12	27.97	0.72
Lebanon	0.13	0.24	0.11	0.06	0.10	26.23	0.30	0.13	0.25	0.12	0.06	0.11	32.26	3.60
Turkey	0.15	0.30	0.21	0.16	0.14	30.25	-1.15	0.18	0.36	0.25	0.19	0.17	35.25	6.75
High														
Bahrain	0.17	0.33	0.21	0.14	0.16	30.77	-1.42	0.20	0.39	0.25	0.17	0.19	34.94	-0.73
Cyprus	0.15	0.30	0.15	0.09	0.18	34.91	8.57	0.14	0.28	0.14	0.08	0.17	41.46	-0.65
Israel	0.24	0.32	0.19	0.21	0.24	44.63	5.51	0.20	0.26	0.15	0.17	0.20	50.03	-1.71
Kuwait	0.14	0.29	0.20	0.13	0.11	26.82	0.78	0.19	0.40	0.27	0.17	0.15	30.86	-1.76
Oman	0.17	0.33	0.21	0.14	0.15	28.72	-6.60	0.20	0.39	0.25	0.17	0.18	32.08	-3.79
Qatar	0.14	0.30	0.20	0.13	0.11	31.62	-5.53	0.19	0.40	0.27	0.18	0.15	38.46	-0.51
Saudi Arabia	0.15	0.28	0.20	0.12	0.09	32.56	-4.03	0.22	0.40	0.28	0.18	0.13	41.24	-2.06
United Arab Emirates	0.14	0.31	0.21	0.15	0.15	37.33	-5.31	0.16	0.34	0.23	0.17	0.16	44.39	-3.05
South East Asia and Oceania														
Lower-Middle														
Cambodia	0.15	0.28	0.13	0.08	0.15	21.11	1.51	0.14	0.26	0.12	0.07	0.14	26.12	-3.39
Indonesia	0.14	0.28	0.20	0.12	0.09	23.22	0.80	0.19	0.37	0.27	0.17	0.13	26.11	0.66
Mongolia	0.14	0.29	0.20	0.13	0.11	27.00	-0.77	0.19	0.40	0.27	0.17	0.15	31.03	7.01
Philippines	0.14	0.27	0.19	0.12	0.09	24.28	7.26	0.19	0.37	0.26	0.16	0.12	27.84	-3.32
Viet Nam	0.13	0.26	0.12	0.06	0.12	26.19	6.34	0.13	0.26	0.12	0.06	0.12	31.96	1.77
Upper-Middle	*0.18*	*0.30*	*0.20*	*0.16*	*0.16*	*35.06*	*6.03*	*0.19*	*0.33*	*0.22*	*0.17*	*0.16*	*40.82*	*-0.75*
China	0.15	0.33	0.20	0.17	0.16	39.35	13.95	0.17	0.35	0.22	0.18	0.17	45.67	-2.97
Malaysia	0.25	0.30	0.20	0.18	0.23	37.36	1.05	0.20	0.25	0.16	0.15	0.19	42.59	0.31
Thailand	0.14	0.28	0.20	0.13	0.10	28.48	3.09	0.19	0.38	0.27	0.18	0.13	34.21	0.42
High	*0.16*	*0.32*	*0.18*	*0.13*	*0.17*	*47.70*	*1.47*	*0.17*	*0.34*	*0.19*	*0.14*	*0.18*	*55.72*	*-1.52*
Australia	0.16	0.32	0.18	0.17	0.21	48.57	-5.74	0.16	0.31	0.17	0.17	0.20	54.02	2.25
Hong Kong (China)	0.15	0.31	0.15	0.08	0.18	46.02	-1.55	0.14	0.28	0.14	0.08	0.17	52.93	4.76
Japan	0.17	0.33	0.21	0.16	0.16	48.79	3.17	0.19	0.38	0.25	0.18	0.19	58.87	-9.24
Korea, Republic of	0.16	0.32	0.20	0.15	0.16	48.73	6.43	0.19	0.38	0.23	0.18	0.19	58.61	-8.56

New Zealand	0.16	0.33	0.21	0.14	0.15	44.68	-1.08	0.19	0.39	0.25	0.17	0.18	54.48	2.67
Singapore	0.15	0.30	0.14	0.09	0.17	49.44	7.62	0.13	0.27	0.13	0.08	0.16	55.38	-0.97
Sub-Saharan Africa														
Low														
Benin	0.18	0.34	0.22	0.15	0.18	19.78	-3.74	0.18	0.35	0.22	0.15	0.18	22.74	-3.05
Burkina Faso	0.15	0.28	0.19	0.11	0.10	20.18	1.15	0.20	0.38	0.26	0.15	0.14	21.37	-8.62
Burundi	0.14	0.26	0.18	0.11	0.09	19.22	-3.98	0.21	0.39	0.27	0.17	0.13	18.85	1.49
Ethiopia	0.25	0.29	0.19	0.16	0.20	16.57	0.97	0.22	0.26	0.17	0.14	0.18	20.85	7.42
Guinea	0.19	0.34	0.23	0.16	0.19	12.25	0.10	0.19	0.35	0.24	0.16	0.19	13.77	2.82
Madagascar	0.13	0.23	0.10	0.05	0.10	20.15	-3.92	0.14	0.25	0.11	0.06	0.10	23.97	2.16
Malawi	0.18	0.34	0.23	0.16	0.18	18.09	6.13	0.18	0.34	0.23	0.16	0.18	20.87	2.00
Mali	0.15	0.32	0.21	0.14	0.13	17.80	9.10	0.18	0.39	0.26	0.17	0.16	18.78	-3.58
Mozambique	0.15	0.31	0.15	0.09	0.19	24.45	4.76	0.14	0.28	0.14	0.08	0.17	29.84	-6.03
Niger	0.18	0.34	0.23	0.16	0.18	19.39	3.70	0.18	0.34	0.23	0.16	0.18	22.38	-9.90
Rwanda	0.25	0.29	0.20	0.19	0.24	28.62	-4.57	0.21	0.25	0.17	0.17	0.21	34.41	-7.14
Senegal	0.15	0.30	0.22	0.16	0.13	19.41	3.71	0.18	0.37	0.26	0.20	0.16	20.86	2.73
Tanzania, United Republic of	0.28	0.25	0.19	0.15	0.19	16.91	0.09	0.28	0.25	0.19	0.15	0.19	20.18	10.12
Togo	0.15	0.29	0.18	0.12	0.09	17.67	0.47	0.19	0.38	0.24	0.16	0.12	18.02	-7.03
Uganda	0.25	0.27	0.19	0.13	0.18	22.91	0.56	0.23	0.25	0.17	0.12	0.17	27.99	-3.59
Lower-Middle														
Cameroon	0.18	0.35	0.23	0.16	0.18	17.95	1.45	0.18	0.35	0.23	0.16	0.18	20.74	0.49
Cote d'Ivoire	0.19	0.36	0.24	0.17	0.19	15.98	11.12	0.18	0.34	0.23	0.16	0.18	19.03	0.47
Ghana	0.14	0.28	0.14	0.08	0.14	23.82	-0.28	0.14	0.27	0.13	0.07	0.14	29.12	-4.09
Kenya	0.15	0.30	0.21	0.16	0.13	20.56	1.74	0.18	0.37	0.26	0.20	0.16	22.05	8.62
Nigeria	0.14	0.29	0.20	0.13	0.11	17.52	0.36	0.19	0.40	0.28	0.18	0.15	17.05	3.12
Zambia	0.25	0.32	0.20	0.12	0.21	5.76	9.84	0.23	0.29	0.18	0.11	0.19	8.03	7.47
Upper-Middle														
Botswana	0.14	0.28	0.20	0.14	0.10	27.33	-3.55	0.17	0.34	0.25	0.17	0.12	32.42	-8.19
Mauritius	0.14	0.26	0.19	0.11	0.09	28.65	-2.11	0.21	0.39	0.28	0.17	0.13	34.49	-1.87
Namibia	0.15	0.27	0.13	0.07	0.14	23.72	-9.80	0.14	0.26	0.13	0.07	0.13	28.52	2.83
South Africa	0.14	0.31	0.20	0.13	0.12	30.31	-0.89	0.19	0.40	0.26	0.17	0.16	35.83	-2.73

Robustness exercise on the choice of PLS

Following a reviewer's recommendation, we compare the performance of the PLS regression against a multi-layer perceptron (MLP), as a robustness check. MLP is a feed-forward neural network, which, due to its non-linear nature, can fit the data closely. The sum of squared error produced by the MLP can therefore serve as a benchmark for performance comparison to examine whether competing models can approximate the underlying data model adequately. We provide here further details of the robustness exercise and explain its limitations.

Regarding the architecture of the neural network, we use 5 inputs, 2 outputs and one hidden layer. For the training of the MLP we considered a randomized training set (60% of the sample), validation set (20% of the sample), and test set (20% of the sample). To obtain the minimum possible SSE, we vary the number of nodes and initial conditions, through an iterative procedure. In particular, for each number of nodes from 1 to 10, we fit the MLP 100 times and obtain the minimum SSE produced. That is, 10 minimum SSEs are generated, each corresponding to a different number of nodes. The overall minimum SSE that results from this process is 8.07. We find that PLS, with an SSE of 9.27 when applied to the full set of countries, performs close to the benchmark.

The outperformance of PLS from the MLP is expected, given that one of the advantages of MLP is that it can predict any function, to any degree of accuracy with very mild assumptions. Thus, one does not need to hand-pick the model; it can be completely data-driven, and thus more accurate, especially for methods that rely on correct specification. However, one of the main research objectives of this study is to estimate the country-specific sensitivities of innovation outputs to changes in innovation inputs. This type of analysis requires the estimation of coefficients obtained by running a local regression, such as the local PLS framework used in this paper. The degree of localization is allowed to vary from 7 countries to 120, while the optimal size of the neighborhood that is used in our PLS estimation is 44 countries. There are two main reasons for which, after careful consideration, we concluded that local PLS is more suitable in addressing the specific research objectives, when compared to competing approaches such as MLP, despite the closer fit to the data.

First, using MLP, the interpretability of the coefficients is obscured. While in a linear and PLS regression, for example, we can interpret the coefficients as marginal effects, this is not the case with MLP since interpretation is very complicated and strongly depends on the architecture and the activation functions of the network. A neural network can put a weight of 0 or close to 0 to some variables that actually affect the dependent variables, but they are not useful for prediction. If the same experiment is repeated, sometimes the network will put a small weight to some group of variables, and other times to a different group of variables. This does not affect the prediction accuracy, but it shows that the interpretation of the weights of the MLP is not so straightforward. Therefore, one reason for choosing a local PLS Regression framework is that with PLS we can easily obtain interpretable betas for each country, in line with our paper objectives.

Second, even if we assumed that this difficulty could be surpassed, MLP has increased data requirements due to the number of parameters that need to be estimated. Therefore, with 5 inputs, 1 hidden layer and 2 outputs, it would not be a good practice fitting an MLP to the relatively small neighborhood-driven (sub)samples we use in the local PLS regressions. To be precise, while MLP would still fit the data, its lack of parsimony renders it problematic as an inferential tool on this occasion given the problem of overfitting. Even if overfitting was not an issue in this case, there would be issues with converging towards local rather than global minima, with the important consequence of estimating a different model for each subset. Quite importantly, the SSEs arising from running various MLPs locally rather than globally would not be comparable, unless significant restrictions were to be imposed, compromising the performance of the MLP and negating the point of the whole exercise. For these reasons, PLS appears to be a safer and more stable choice when applied locally to our data compared to MLP.

To alleviate to some extent the issues described above, we limited the robustness exercise to assess the performance of the PLS applied on the full data set, rather than the local PLS regressions. We conclude that the SSE of 9.27 that PLS produces, is close to the MLP benchmark of 8.07.

Table S5. Rank correlations between input pillars and GII scores

The table presents the rank correlations between innovation inputs and outputs, while the last line reports in bold the correlations between the input-output variables and the GII scores.

	Institutions	Human Capital & Research	Infrastructure	Market Sophistication	Business Sophistication	Knowledge & Technology	Creative Outputs	GII Score
Institutions	1							
Human Capital & Research	0.778	1						
Infrastructure	0.843	0.849	1					
Market Sophistication	0.682	0.680	0.699	1				
Business Sophistication	0.700	0.678	0.673	0.641	1			
Knowledge & Technology	0.781	0.799	0.813	0.681	0.726	1		
Creative Outputs	0.699	0.773	0.743	0.625	0.719	0.934	1	
GII Score	**0.883**	**0.883**	**0.902**	**0.775**	**0.777**	**0.959**	**0.892**	**1**

Table S6. Rank correlations between innovation efficiency and GII scores

The table presents the rank correlations between the MEA efficiency scores of innovation inputs and outputs, while the last line reports in bold the correlations between efficiency and GII scores.

	Institutions	Human Capital & Research	Infrastructure	Market Sophistication	Business Sophistication	Knowledge & Technology	Creative Outputs	GII Score
Institutions	1							
Human Capital & Research	0.948	1						
Infrastructure	0.894	0.906	1					
Market Sophistication	0.873	0.906	0.868	1				
Business Sophistication	0.882	0.910	0.834	0.867	1			
Knowledge & Technology	0.864	0.906	0.856	0.929	0.863	1		
Creative Outputs	0.914	0.892	0.845	0.793	0.914	0.762	1	
GII Score	**0.314**	**0.228**	**0.270**	**0.355**	**0.302**	**0.238**	**0.259**	**1**

Table S7. Rank correlations between sensitivities and GII scores

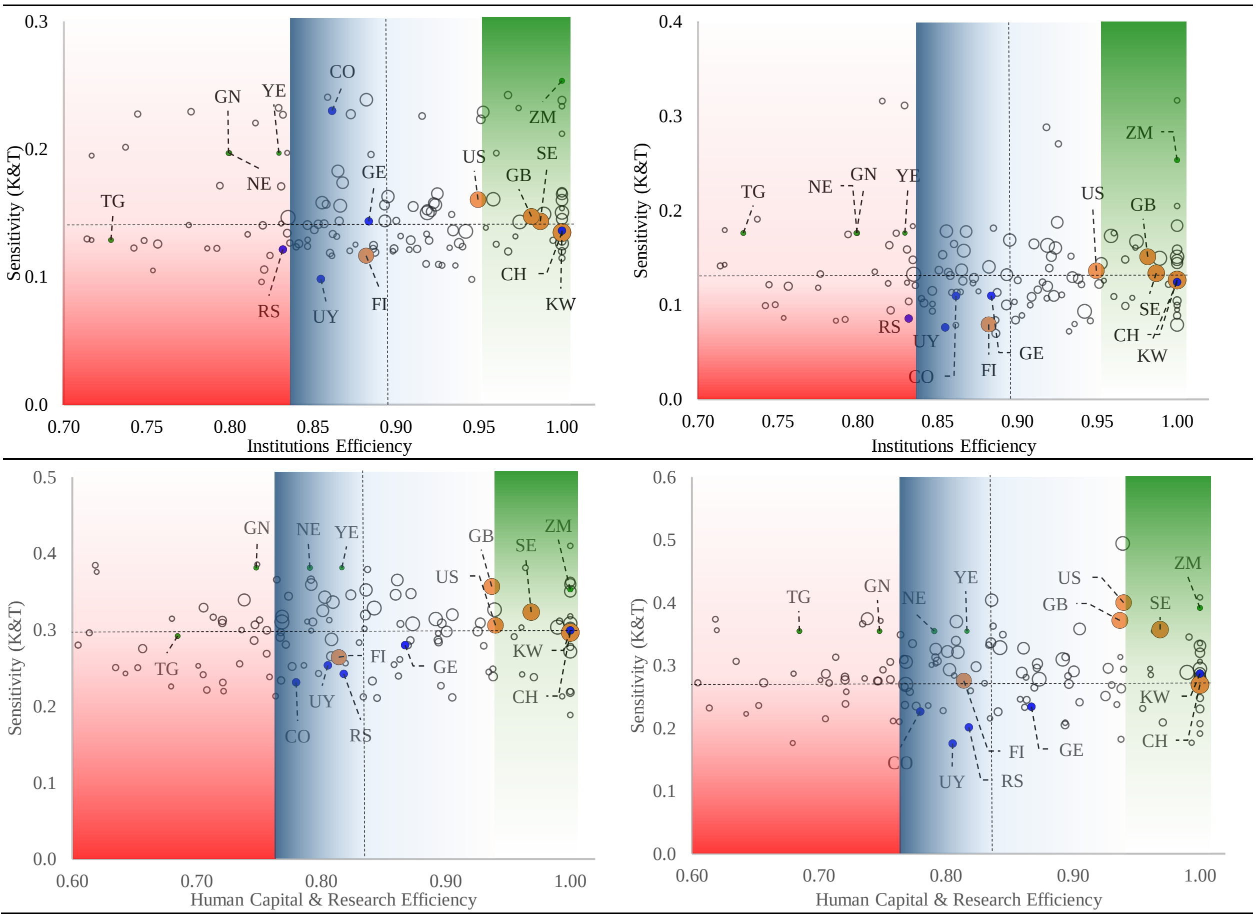
The table presents rank correlations between the input sensitivities of the *Knowledge & Technology* (K&T) and *Creative Outputs* (Cr). The boxed section reports the cross correlations while the last line presents in bold the correlations between sensitivities and the GII scores.

	Institutions (K&T)	Human Capital & Research (K&T)	Infrastructure (K&T)	Market Sophistication (K&T)	Business Sophistication (K&T)	Institutions (Cr)	Human Capital & Research (Cr)	Infrastructure (Cr)	Market Sophistication (Cr)	Business Sophistication (Cr)	GII Score
Institutions (K&T)	1										
Human Capital & Research (K&T)	0.490	1									
Infrastructure (K&T)	0.335	0.678	1								
Market Sophistication (K&T)	0.622	0.618	0.724	1							
Business Sophistication (K&T)	0.790	0.523	0.120	0.467	1						
Institutions (Cr)	0.546	0.045	0.344	0.468	0.046	1					
Human Capital & Research (Cr)	-0.151	0.375	0.488	0.156	-0.458	0.328	1				
Infrastructure (Cr)	-0.109	0.174	0.578	0.279	-0.498	0.530	0.883	1			
Market Sophistication (Cr)	0.112	0.443	0.685	0.645	-0.161	0.423	0.719	0.772	1		
Business Sophistication (Cr)	0.782	0.776	0.473	0.710	0.811	0.308	0.078	0.014	0.345	1	
GII Score	**0.101**	**0.292**	**-0.050**	**0.195**	**0.269**	**-0.154**	**0.012**	**-0.119**	**0.220**	**0.323**	**1**

Figure S4.[18] Results for IPR protection – *Knowledge & Technology Outputs*

The figures below present the scatterplots of input efficiencies and marginal contributions with respect to the *Knowledge & Technology Outputs*. The left panel shows the original scatterplots, while in the right panel we present the results of our model when intellectual property rights (IPR) protection is added in the set of environmental variables that defines the nearest neighbours of each country. We obtain data from the Global Competitiveness Report 2016, which cites the World Economic Forum, Executive Opinion Survey. The values for each country correspond to average responses of executives to the question: “In your country, to what extent is intellectual property protected? [1 = not at all; 7 = to a great extent]”. IPR protection is an institutional factor with cited importance for innovation as well as for its links with R&D intensity and FDI (Grossman & Lai, 2004; Helpman, 1993; Lerner, 2009; Maskus, Milani, & Neumann, 2019). Therefore, while this factor provisions a role for institutions in our framework, it is still consistent with the internationalization orientation that we adopt in this study. Further explanations about the figures can be found in the notes of Figure 2 in the main text. We find that the estimated sensitivities are quite robust to the alternative specification in that the majority of the example countries are located in nearby regions compared to the original results. Moreover, given that input efficiencies are not varied in this exercise, the countries’ position with respect to the three proposed policies remains unaffected. Overall, the empirical findings and policy implications of our paper remain unaffected.

Original	*With IPR protection*



[18] The authors would like to thank an anonymous referee for suggesting to consider additional factors in the environment.

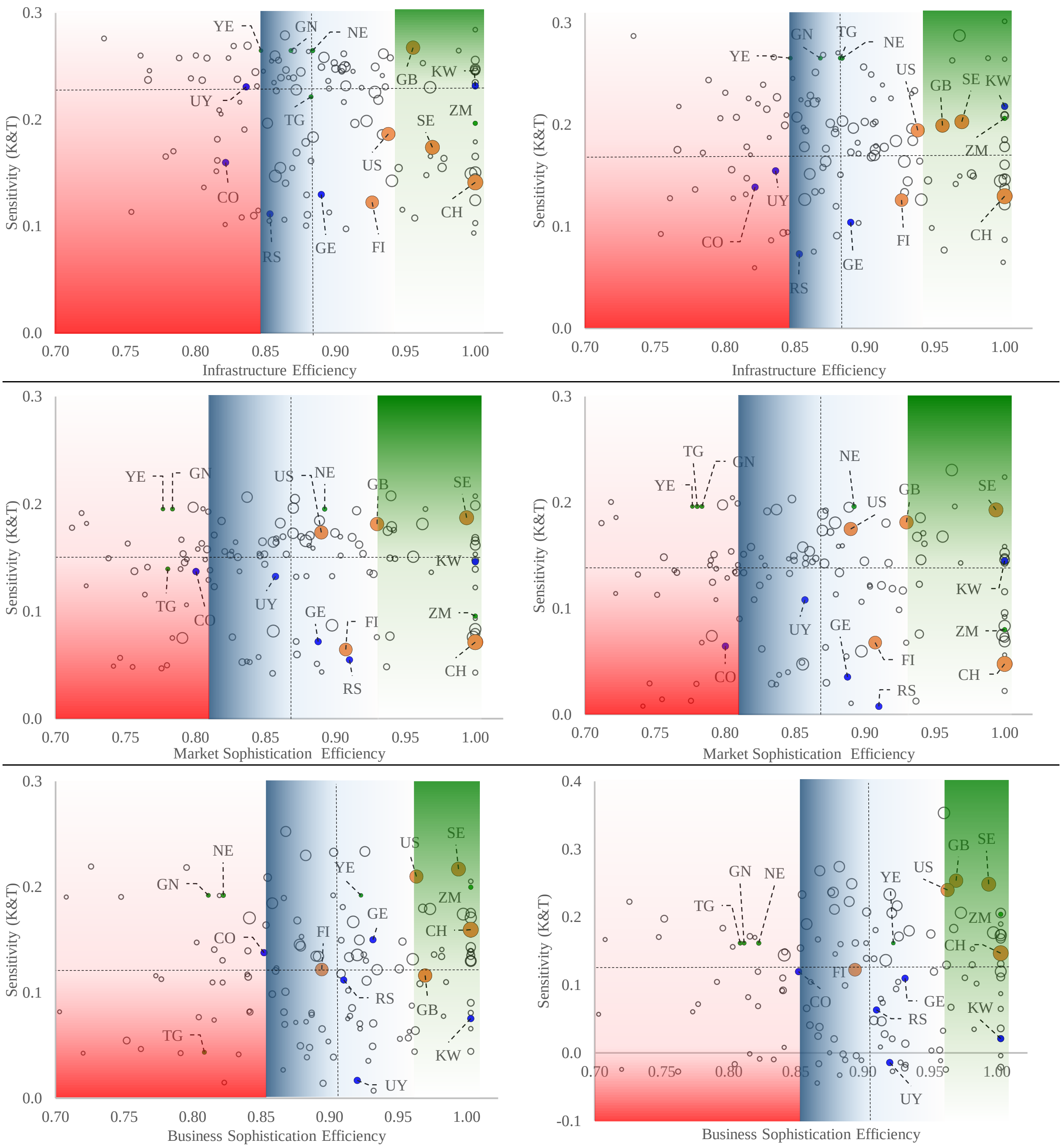
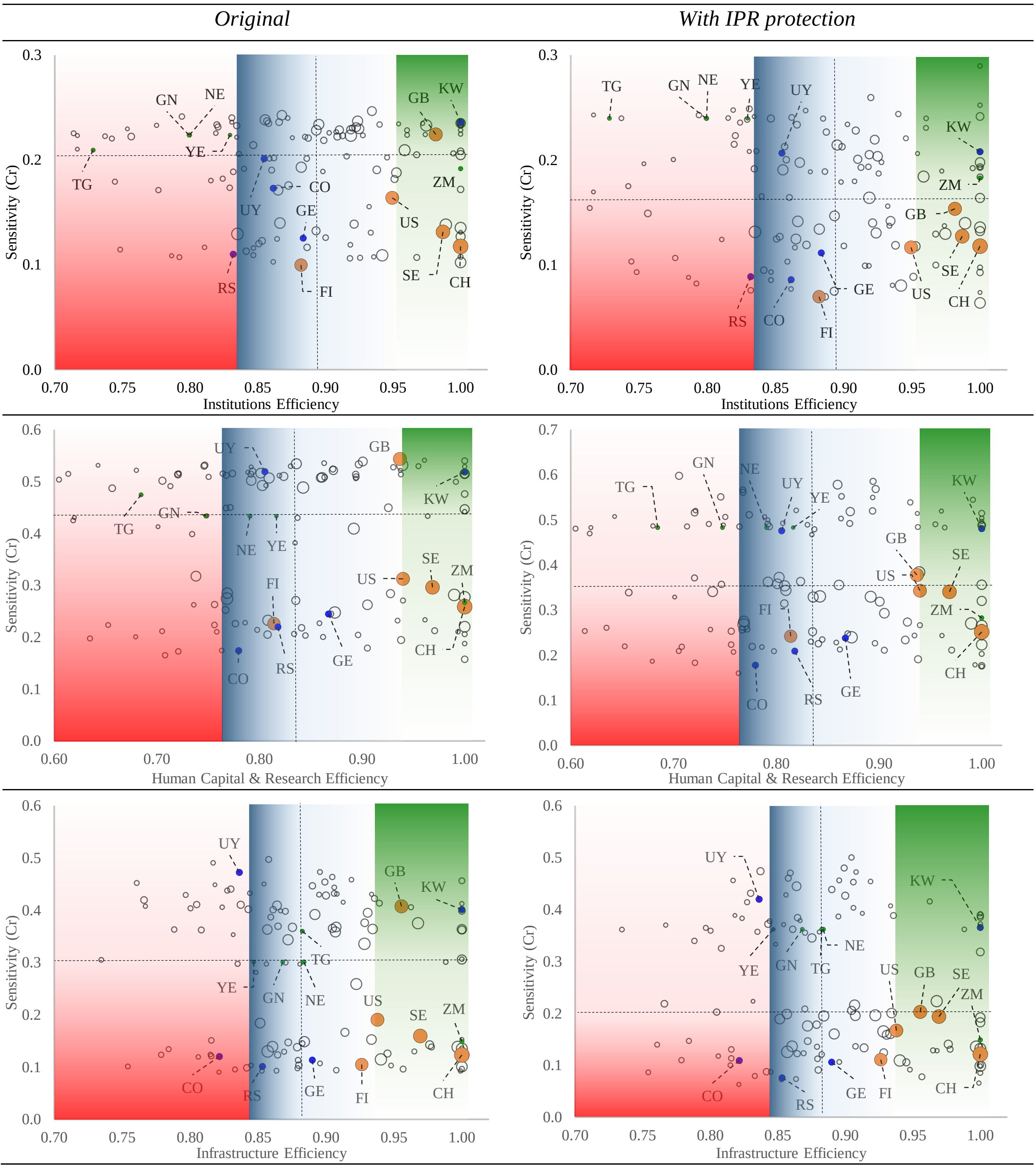
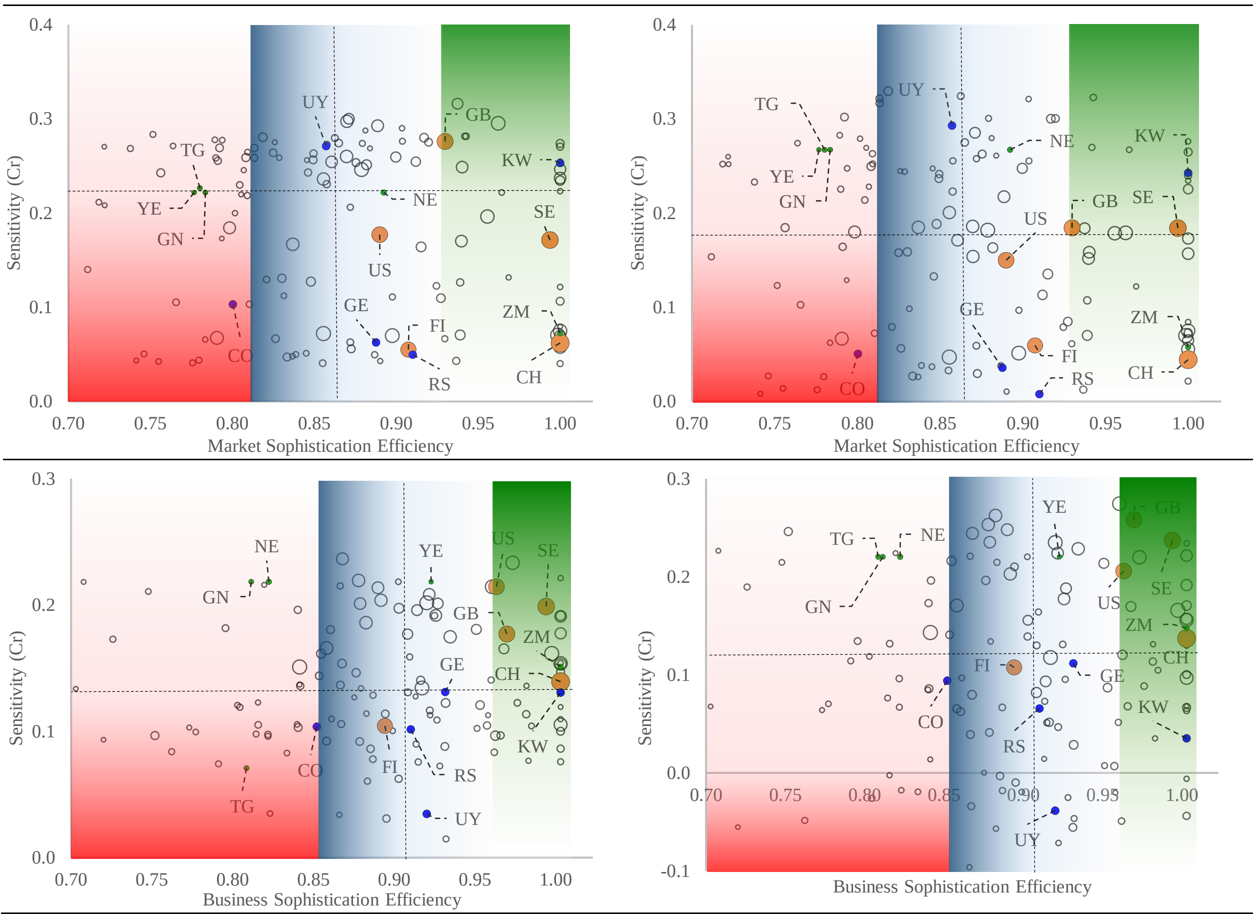

Sensitivity (K&T)
Infrastructure Efficiency
YE
GN
NE
UY
TG
GB
KW
SE
ZM
US
CO
RS
GE
FI
CH
Market Sophistication Efficiency
Business Sophistication Efficiency

Figure S5. Results for IPR protection - *Creative Outputs*

The figures below present the scatterplots of input efficiencies and marginal contributions with respect to the *Creative Outputs*. Full details are provided below Figure S4.

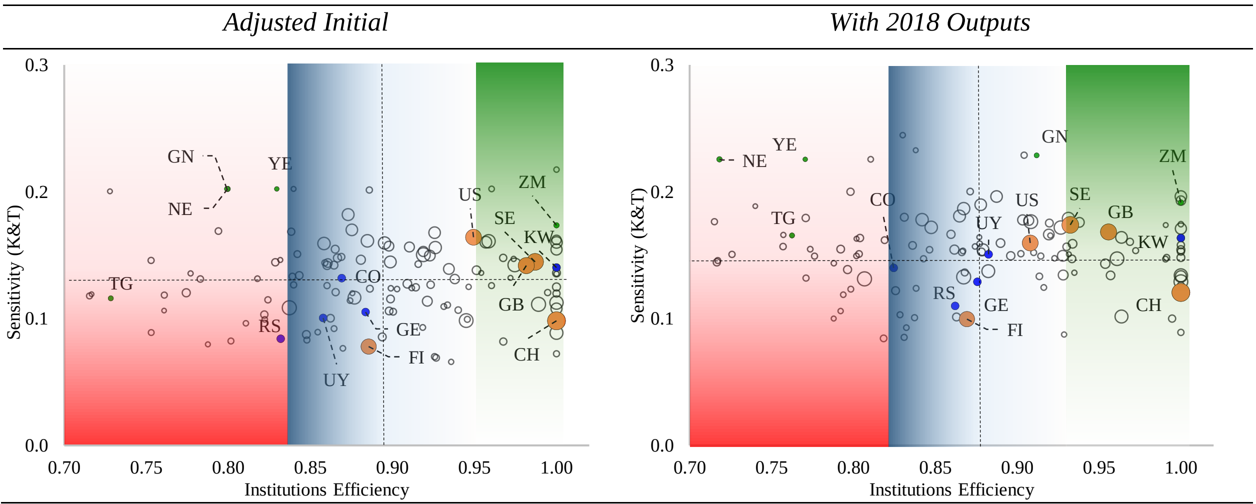




Sensitivity (Cr)
Market Sophistication Efficiency
Business Sophistication Efficiency
0.0
0.1
0.2
0.3
0.4
-0.1
0.70
0.75
0.80
0.85
0.90
0.95
1.00
UY
GB
TG
KW
YE
NE
GN
SE
US
GE
FI
ZM
CO
RS
CH

Figure S6.[19] Sensitivities and MEA scores using 2018 *Knowledge & Technology Outputs*

The figures below present the scatterplots of input efficiencies and marginal contributions with respect to the *Knowledge & Technology Outputs* of year 2018, using the inputs of 2016. Further explanations about the figures can be found in the notes of Figure 2 in the main text. The purpose of this exercise is to examine the potential lagged responses of innovation outputs to innovation inputs, since the conversion of related investments to commercially adopted innovations can take time (Cruz-Cázares et al., 2013). Year 2018 was chosen due to data availability as it is the year which includes the most countries in common with 2016. For two countries (Ethiopia and Nicaragua) which did not appear in the 2018 GII rankings, data on innovation outputs was used from 2019, while we note that this modification does not affect the MEA results as they were not innovation-efficient. Moreover, given that Bhutan and Venezuela do not appear in any of the subsequent reports and due to the fact that Venezuela is innovation-efficient in 2016, all results were estimated again by excluding these two countries to facilitate such a comparison (column "Adjusted Initial" below). The results of the exercise appear in the second column, where it is shown that the majority of the example countries are located in nearby regions compared to the initial case. It is interesting to note that the estimated sensitivities are quite robust, suggesting that the estimation within each neighbourhood is relatively unaffected in this exercise. However, it is important to highlight the limitations of this cross-period exercise using the GII scores, which are outlined in the GII report (GII, 2016, p. 58). First, the list of indicators or the definition of variables may be reconsidered from year to year, affecting scores and rankings accordingly. Second, data availability issues result in missing values for certain countries for some of the variables used, while this may even lead to the exclusion of a country from the GII report altogether, according to the data completeness criteria followed. In either case, this could affect the normalisation process and therefore the respective pillar scores and rankings. Finally, the data used in the GII report refer to several years rather than a fixed one, depending on the latest available data (GII, 2016, 393), while the years used for the different variables may also refer to different years. Therefore, observed changes in pillar scores from one year to another may be due to various factors and the results of any cross-period exercise should be interpreted with caution.



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[19] The authors would like to thank an anonymous referee for recommending a lagged response exercise.

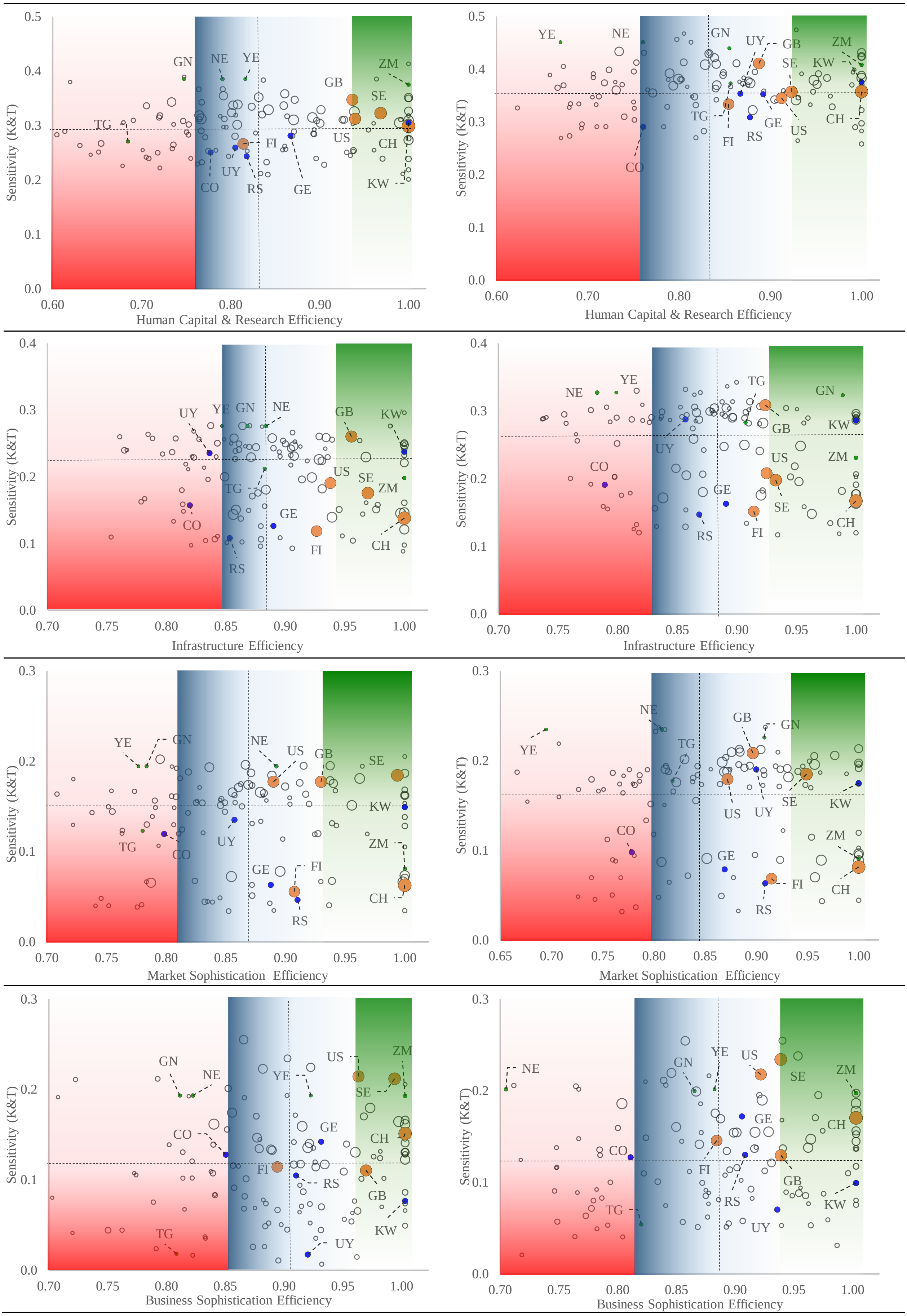
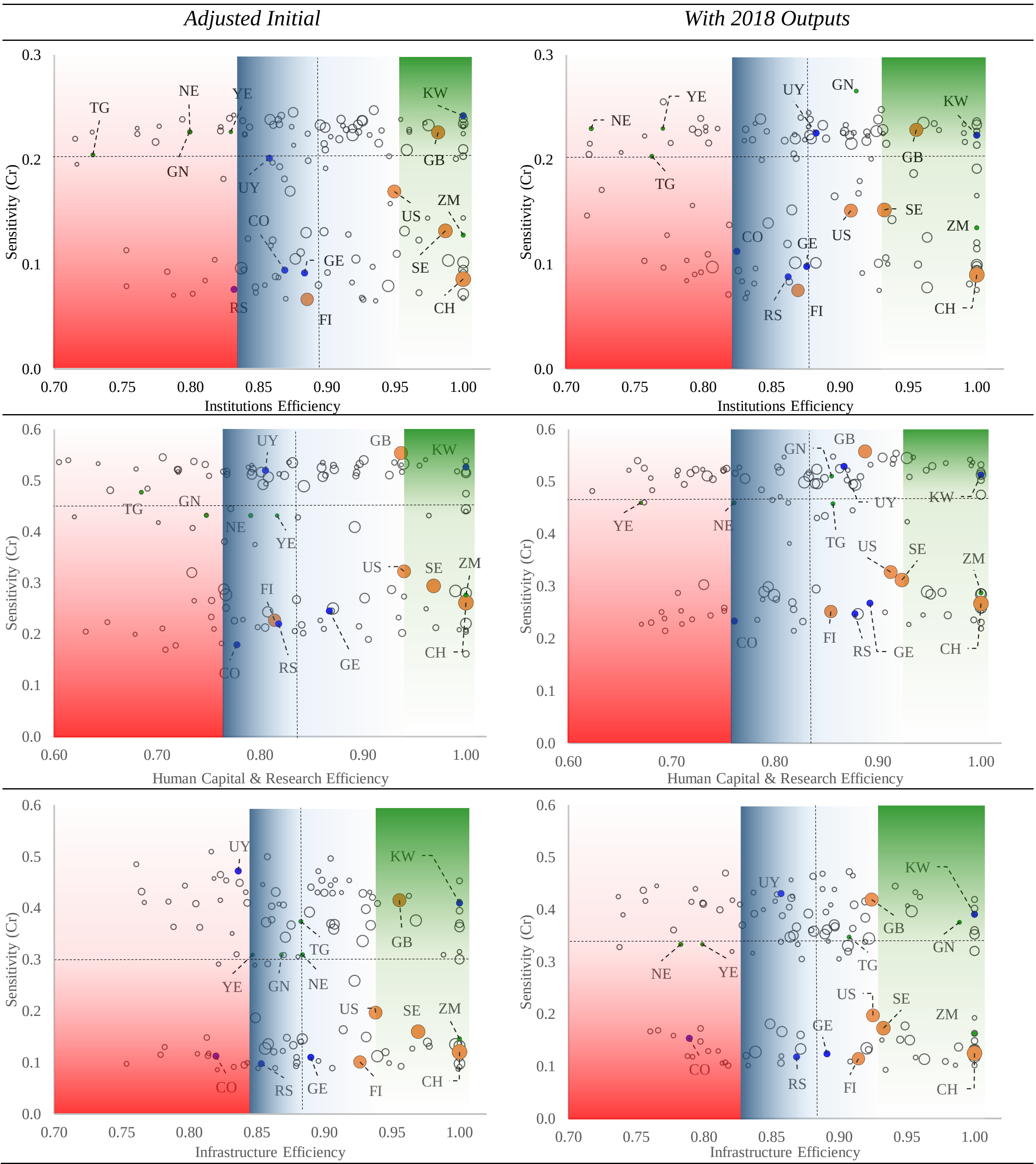
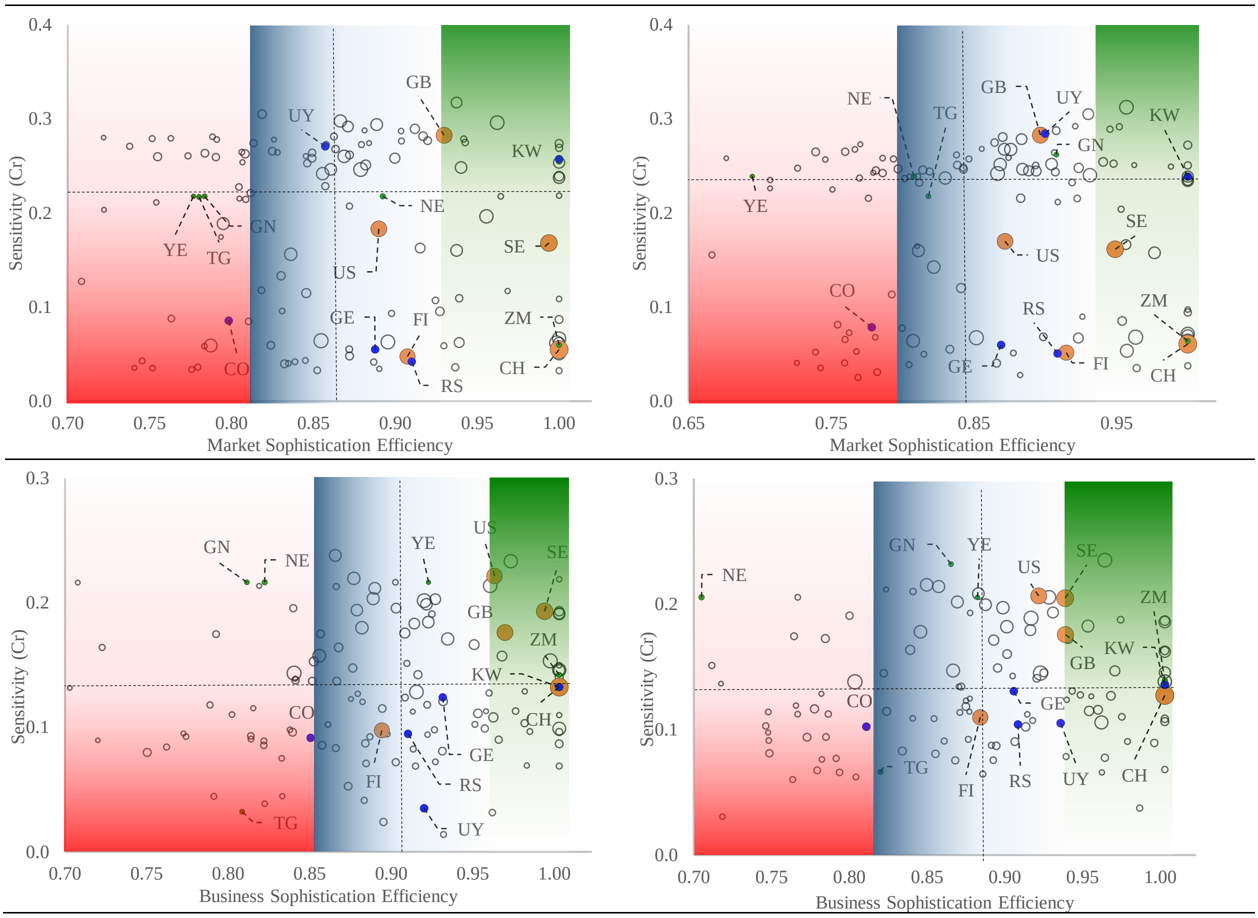

Sensitivity (K&T)
Human Capital & Research Efficiency
GN NE YE ZM GB SE TG US CH FI UY CO RS GE KW
Human Capital & Research Efficiency
YE NE GN UY GB ZM SE KW TG GE RS US CH FI CO
Infrastructure Efficiency
UY YE GN NE GB KW US SE ZM TG GE FI CO RS CH
Infrastructure Efficiency
NE YE TG GN GB KW UY US ZM CO GE SE FI RS CH
Market Sophistication Efficiency
YE GN NE US GB SE KW TG CO UY ZM GE FI RS CH
Market Sophistication Efficiency
NE GB GN YE TG US UY SE KW CO ZM GE FI RS CH
Business Sophistication Efficiency
GN NE US ZM YE SE CO GE CH FI RS GB KW TG UY
Business Sophistication Efficiency
NE GN YE US SE ZM CH GE CO FI GB RS KW TG UY

Figure S7. Sensitivities and MEA scores using 2018 *Creative Outputs*

The figures below present the scatterplots of input efficiencies and marginal contributions with respect to the *Creative Outputs* of year 2018, using though the 2016 inputs. Full details are provided below Figure S6.





0.4
0.3
0.2
0.1
0.0
Sensitivity (Cr)
GB
UY
KW
NE
GN
YE
TG
SE
US
GE
FI
ZM
CO
CH
RS
0.70
0.75
0.80
0.85
0.90
0.95
1.00
Market Sophistication Efficiency
0.4
0.3
0.2
0.1
0.0
Sensitivity (Cr)
NE
TG
GB
UY
GN
KW
YE
SE
US
CO
RS
ZM
GE
FI
CH
0.65
0.75
0.85
0.95
Market Sophistication Efficiency
0.3
0.2
0.1
0.0
Sensitivity (Cr)
GN
NE
YE
US
SE
GB
ZM
KW
CO
CH
GE
FI
RS
TG
UY
0.70
0.75
0.80
0.85
0.90
0.95
1.00
Business Sophistication Efficiency
0.3
0.2
0.1
0.0
Sensitivity (Cr)
GN
YE
NE
US
SE
ZM
KW
GB
CO
GE
TG
FI
RS
UY
CH
0.70
0.75
0.80
0.85
0.90
0.95
1.00
Business Sophistication Efficiency

Table S8. Country name abbreviations and income groups

Central and Southern Asia	CSA	Income
Bangladesh	BD	LM
Bhutan	BT	LM
India	IN	LM
Iran, Islamic Republic of	IR	UM
Kazakhstan	KZ	UM
Kyrgyzstan	KG	LM
Nepal	NP	L
Pakistan	PK	LM
Sri Lanka	LK	LM
Tajikistan	TJ	LM

Latin America and the Caribbean	LCA	Income
Argentina	AR	UM
Bolivia, Plurinational State of	BO	LM
Brazil	BR	UM
Chile	CL	H
Colombia	CO	UM
Costa Rica	CR	UM
Dominican Republic	DO	UM
Ecuador	EC	UM
El Salvador	SV	LM
Guatemala	GT	LM
Honduras	HN	LM
Jamaica	JM	UM
Mexico	MX	UM
Nicaragua	NI	LM
Panama	PA	UM
Paraguay	PY	UM

Europe	EU	Income
Albania	AL	UM
Austria	AT	H
Belarus	BY	UM
Belgium	BE	H
Bosnia and Herzegovina	BA	UM
Bulgaria	BG	UM
Croatia	HR	H
Czech Republic	CZ	H
Denmark	DK	H
Estonia	EE	H
Finland	FI	H
France	FR	H
Germany	DE	H
Greece	GR	H
Hungary	HU	H
Iceland	IS	H
Ireland	IE	H
Italy	IT	H
Latvia	LV	H
Lithuania	LT	H
Luxembourg	LU	H
Malta	MT	H
Moldova, Republic of	MD	LM
Montenegro	ME	UM
Netherlands	NL	H
Norway	NO	H
Poland	PL	H
Portugal	PT	H

Northern Africa and Western Asia	NAWA	Income
Algeria	DZ	UM
Armenia	AM	LM
Azerbaijan	AZ	UM
Bahrain	BH	H
Cyprus	CY	H
Egypt	EG	LM
Georgia	GE	UM
Israel	IL	H
Jordan	JO	UM
Kuwait	KW	H
Lebanon	LB	UM
Morocco	MA	LM
Oman	OM	H
Qatar	QA	H
Saudi Arabia	SA	H
Tunisia	TN	LM
Turkey	TR	UM
United Arab Emirates	AE	H
Yemen	YE	LM

South East Asia and Oceania	SEAO	Income
Australia	AU	H
Cambodia	KH	LM
China	CN	UM
Hong Kong (China)	HK	H
Indonesia	ID	LM
Japan	JP	H
Korea, Republic of	KR	H

Sub-Saharan Africa	SSF	Income
Benin	CH	L
Botswana	BW	UM
Burkina Faso	BF	L
Burundi	BI	L
Cameroon	CM	LM
Côte d'Ivoire	CI	LM
Ethiopia	ET	L
Ghana	GH	LM
Guinea	GN	L
Kenya	KE	LM
Madagascar	MG	L
Malawi	MW	L
Mali	ML	L
Mauritius	MU	UM
Mozambique	MZ	L
Namibia	NA	UM
Niger	NE	L
Nigeria	NG	LM
Rwanda	RW	L
Senegal	SN	L
South Africa	ZA	UM
Tanzania, United Republic of	TZ	L
Togo	TG	L
Uganda	UG	L
Zambia	ZM	LM

Peru	PE	UM	Romania	RO	UM	Malaysia	MY	UM
Uruguay	UY	H	Russian Federation	RU	UM	Mongolia	MN	LM
Venezuela, Bolivarian Republic of	VE	UM	Serbia	RS	UM	New Zealand	NZ	H
			Slovakia	SK	H	Philippines	PH	LM
Northern America	**NA**	**Income**	Slovenia	SI	H	Singapore	SG	H
Canada	CA	H	Spain	ES	H	Thailand	TH	UM
United States of America	US	H	Sweden	SE	H	Viet Nam	VN	LM
			Switzerland	CH	H			
			TFYR Macedonia	MK	UM			
			Ukraine	UA	LM			
			United Kingdom	GB	H			