ARTICLE

DOI 10.52781/cmm.a070

Anomalies Detection in the Global Innovation Index's Indicators

Detección de anomalías en los indicadores del Índice Global de Innovación

Abstract: The measurement of a country's innovation capacity is essential for studies of trends and the identification of bottlenecks in a National Innovation System (NIs). In this context, the indicators utilized by the Global Innovation Index (GII) are crucial, since they support various researches and strategic decisions by investors, entrepreneurs and public agents. However, GII indicators are impacted by methodological changes and suffer from several types of practical problems such as measurement errors or missing data, generating anomalies in analyzes. Based on the premise of innovation incrementalism, the concept of anomaly was defined and a method was developed to automatically detect them, while classifying those resulting from methodological changes in opposition to those resulted from practical problems. The proposed method was applied to the indicators from the innovation outputs of Brazil, from 2013 to 2019, released by the GII.

Keywords: Innovation Index; Incrementalism; Global Innovation Index GII; National Innovation Systems.

Resumen: Medir la capacidad de innovación de un país es fundamental para realizar estudios de tendencias e identificar cuellos de botella en un Sistema Nacional de Innovación (SNI). En esta línea, se destacan los indicadores utilizados por el Índice Global de Innovación (GII), que sustentan diversas encuestas y respaldan las decisiones estratégicas de inversores, emprendedores y agentes públicos. Sin embargo, a lo largo del tiempo, los diversos indicadores de GII sufren cambios metodológicos y adolecen de diversos tipos de problemas prácticos, como falta de datos, lo que dificulta el análisis de tendencias. Partiendo de la premisa del incrementalismo de la innovación, se definió el concepto de anomalías y se diseñó un método para detectarlas automáticamente, además de clasificarlas como resultantes de cambios metodológicos, frente a inconsistencias, que involucran problemas de orden práctica. El método propuesto fue aplicado a los indicadores de los Productos de Innovación de Brasil, de 2013 a 2019, publicados por el GII.

Palabras clave: Indicadores de innovación; Incrementalismo; Índice Global de Innovación GII; Sistemas Nacionales de Innovación.

Juraci Ferreira Galdino
Exército Brasileiro.
Instituto Militar de Engenharia.
Rio de Janeiro, RJ, Brasil.
galdino.juraci@eb.mil.br

José Adalberto França Junior
Agência de Gestão e Inovação Tecnológica (AGITEC).
Rio de Janeiro, RJ, Brasil.
betoordie@gmail.com

Received: Apr. 09, 2021
Approved: Oct. 28, 2021

COLEÇÃO MEIRA MATTOS
ISSN on-line 2316-4891 / ISSN print 2316-4833
http://ebrevistas.eb.mil.br/index.php/RMM/index

1 Introduction

The efficiency of the National Innovation System (NIS) is essential for economic growth (LUNDVALL, 2010) and the development of important technologies to ensure a country's sovereignty (GALDINO, 2019; SCHONS; PRADO FILHO; GALDINO, 2020). Therefore, having reliable indicators capable of evaluating the performance of a country's NIS is fundamental to subsidies studies and analyses aimed at identifying bottlenecks and trends in the NIS (AVELLAR; BRITO, 2015), gathering information to establish policies and strategic actions aimed at increasing innovation capability both nationally and sectorally (SANTOS, 2014; SCHONS; PRADO FILHO; GALDINO, 2021), and evaluating the effectiveness of policies and strategic actions in place (KHEDHAOURIA; THURIK, 2017).

Among the main innovation indicators at the national level, the *Global Innovation Index* (GII) (DUTTA, S. et al. 2018; KOSE; TOPÇU, 2016), which infers the capability of a NIS from an aggregate of about 80 variables, here called baseline variables (BV), stands out.

Innovation indicators, such as those produced by the GII, attract the attention of specialists, public agents, entrepreneurs, and investors. To exemplify the effects that these indicators can produce in the public sphere, we bring up a recent case that occurred in Brazil. Motivated by Brazil's poor results disclosed by the GII indicators, the Brazilian Federal Audit Court (Tribunal de Contas da União – TCU) audited public policies related to the area of innovation and concluded that there was a need for studies to be coordinated by the President's Office and by the Ministry of Science, Technology, Innovation and Communications (BRASIL, 2019) aimed at creating an efficient and effective National Innovation Policy that would be able to improve the country's position in the innovation *ranking* (SCHONS; PRADO FILHO; GALDINO, 2020). The TCU is an example of a public organ that has been expanding its field of action, starting to evaluate not only the formal aspects of the legality of procedures, but also the performance and results achieved by other organs and public entities (GOMES, 2006).

Released annually since 2007, the GII indicators treat innovation broadly, considering in their metrics variables that measure investments in research and development (R&D), invention patents and scientific articles, as well as others that capture information about institutions, infrastructure, human resources and research, market, aspects linked to the business sector and innovation products (DUTTA et al., 2018). The large number of countries evaluated and the availability of a voluminous database make these indices even more attractive for the analysis of a country's innovation capability (KOSE; TOPÇU, 2016), particularly since 2013, when the architecture of the indicators consisting of indices, sub-indices, pillars and sub-pillars was inaugurated.

Despite the maintenance of this architecture, the calculation of the indexes, sub-indexes, pillars, and sub-pillars of the GII depends on base variables that are prone to methodological changes, given the incessant search for improvement in the understanding of the innovation phenomenon and its measurement forms (JANGER et al., 2017). These sometimes expressive changes, such as the inclusion or deletion of baseline variables (DUTTA et al., 2018), generate anomalies in the temporal evolution of indicators (indexes, sub-indexes, pillars, and sub-pillars of GII) that can lead to erroneous conclusions about NIS.

In addition to GII methodological changes, other anomaly-generating factors can compromise the accuracy of trend analyses and capability bottlenecks of an NIS (DUTTA et al., 2018), making it critical to develop procedures capable of gauging on the reliability of baseline variables. An important step in this intent is to detect and classify these anomalies.

Another fundamental aspect in the contextualization of this article comes from the premise that national scope policies tend to provoke incremental effects (FAGERBERG; MOWERY; VERSPAGEN, 2009; GROENEWEGEN; STEEN, 2006; MICALE, 1990; SOGNER, 2009), specifically producing in the NIS long-term effects with slow and gradual changes (NELSON; WINTER, 1982). This premise highlights the importance of analyses that consider indicators from successive years (hereafter called evolutionary analysis) as opposed to those that adopt only indicators from a single year (here defined as static analysis), because they facilitate the study of trends and analysis of the results of innovation policies (FAGERBERG; MOWERY; VERSPAGEN, 2009; GROENEWEGEN; STEEN, 2006; SOGNER, 2009), assisting in the diagnosis of the benefits of innovation strategies on the competitiveness and economic growth of a nation (LUNDVALL, 2007).

Additionally, this premise suggests that there is a "pattern of normality" whereby "reliable indicators" that capture the results of these public policies do not tend to change abruptly over time. In this paper, anomalies refer to abrupt changes in the behavior of innovation indicators in the short term, such as within a year. Under normal conditions, abrupt changes in a country's indicators are unlikely, as they violate the expectation of incremental changes of a NIS over time (NIOSI et al., 1993). The existence of this normality pattern enables the use of time series analysis tools to identify inconsistencies in the innovation indicators, particularly in those of GII.

However, to the best of the authors' knowledge, the studies using GII indicators to analyze trends, bottlenecks, and capability of a NIS disregard or pay little attention to possible problems caused by anomalies in the data used in the analysis. Here, it is argued that these abnormalities can cause erroneous conclusions about the results of policies and strategic actions directed to the area of innovation, harming both analyses and investments and strategic planning. It is necessary to develop procedures capable of making inferences about the reliability of the data before they are used in trend studies. An important step in this intent is to detect and classify the anomalies of the indicators.

In this context, this work aims to conceptualize anomalies, classify their types, and propose a procedure to identify them in an automated way, considering the measurements of the BV of GII. The proposed method is evaluated for Brazil's Innovation Products from 2013 to 2019.

The remainder of this article is organized as follows. Section 2 provides a literature review of studies using GII indicators in static and evolutionary analyses, as well as discusses the existence of anomalies in these indicators and the difficulty they impose on analyses. Section 3 briefly discusses the concept of anomaly in the literature of statistics. Section 4 discusses the premise of incrementalism in National Innovation Systems. Section 5 discusses the methodology adopted in this work. Section 6 presents the case study for the application of the proposed method. Finally, discussions of the results achieved are presented in Section 7 and main conclusions of the work are presented in Section 8.

2 The use of the gii in the analysis of national innovation systems

The performance of a NIS expresses the national innovation capability, defined as the ability of a country to manage its resources to produce new knowledge, transforming it into technologies and products for the benefit of the entire economic system (FAGERBERG; SRHOLEC, 2008). The national innovation capability is assessed not only by the innovation outputs produced by the system itself, but also through the innovation inputs, often resulting from public policies, which are indispensable to create a favorable environment for the generation of innovations (KHEDHAOURIA; THURIK, 2017).

Several studies that rely on the GII indicators are conducted with the aim of analyzing the impact of innovation policies and comparing the innovation capability of countries. For example, from the 2015 GII database, Jankowska, Matysek-Jędrych e Mroczek-Dąbrowska (2017) analyzed the correlation between innovation inputs and outputs and found that 23 countries do not exhibit the expected positive correlation between these factors, among them Poland and Bulgaria. While Poland had high innovation efforts and unsatisfactory products, Bulgaria had the opposite situation.

Considering the 2015 GII data, Crespo e Crespo (2016) identified combinations of indicators that can deliver excellent innovation performance, which differ for high-income versus low-income countries. This study is in line with others that indicate that the public policies necessary to promote innovation should be particularized according to the country's level of development (KONDO, 2001).

Other static analyses are presented in the GII reports. For example, in the 2018 report (DUTTA et al., 2018), it is discussed and compared leading countries in the high- and middle--income economy groups. Based on the data in this report, Saisana, Domínguez-Torreiro, and Vértesy (2018) seek to establish statistical consistency among country inputs, outputs, and classifications, making inferences about anomalies and measurement errors in the data. Similarly, Famalika e Sihombing (2021), based on the GII 2018 data, compared two cluster analysis techniques to group different countries with similar performances.

However, while static analysis can make inferences about a country's innovation capability at a given point in time, it is especially limited for trend studies. In order to overcome these difficulties, it is necessary to use analyses that consider time series of indicators. Regardless of the benefits, evolutionary analyses are quite complex because of the anomalies.

Using the approach known as *Fuzzy*-set Qualitative Comparative Analysis (fsQCA) methodology (RAGIN, 2008), Khedhaouria and Thurik (2017) arrived at different combinations of innovation inputs that provide the greatest impact on national innovation capability. To do this, they analyzed the GII database between 2012 and 2015. However, they mentioned that the lack of some indicators and the occurrence of anomalies made it impossible to conduct a more comprehensive survey.

Milenkovic et al. (2019) analyzed the correlation between GII and SSI (Social Sustainability Index) indicators for the period from 2010 to 2016. The authors reported difficulties in conducting the study because of changes in GII variables and methodologies after 2010.

Based on the GII indicators from 2008 to 2013, Franco e Oliveira (2017) analyzed the NIS performance of the countries that make up the so-called BRICS (Brazil, Russia, India, China, and South Africa). In this study, the authors used a regression analysis to determine the correlation between innovation inputs and innovation outputs and inferred the impact of each indicator on the country's *ranking* in the GII. However, the authors encountered methodological changes and other anomalies present in the GII reports from 2008 to 2013.

Using the GII indicators from 2013 to 2017, Galdino (2018) performed trend analysis of NIS by grouping countries into quartiles according to the value of innovation indicators. Despite the important findings, this work did not detect, classify, or treat the anomalies. Employing the same indicators, Galdino (2019a) identified bottlenecks and trends in the Innovation Inputs of Brazil's NIS. In this study, the author was faced with missing data, methodological changes from GII, and variables with abnormal values. To try to overcome the effects of these problems in identifying bottlenecks and trends, counterfactual exercises were performed. However, he did not generalize the procedure adopted, nor did he propose a technique to identify anomalies and treat the problems identified automatically; an empirical procedure was adopted.

Drawing on data from China's *World Economic Forum* from 1996 to 2012, Wang, Zhao e Zhang (2016) analyzed China's NIS with a focus on the time lag between investments in innovation input and outputs in terms of innovation outputs. In this study, the authors found missing data in the variable that measures the collaboration between industry and academia for the period 1996 to 2006 and filled in the time series considering 2007 data as missing values, without discussing the effects and justifications as to the relevance of this procedure.

The GII itself recognizes, in its Annex 2, the existence of the factors that generate anomalies in its base variables and therefore recommends caution in the evolutionary analyses (DUTTA; LAVIN; WUNSCH-VICENT, 2017). For example, in the 2017 report, an evolutionary analysis of the performance of the top ten countries over the previous five years is conducted. In this analysis, significant changes in the Netherlands' *ranking* are observed, particularly, between the years 2015 and 2017, and it is commented that this may have occurred as a result of methodology changes or lack of data, suggesting that the abrupt change in the Netherlands' position in the world *ranking*s would not be reliable. However, GII does not delve into the analysis of this issue, nor does it discuss how to solve any anomaly problems (DUTTA et al., 2018).

Finally, in an attempt to avoid anomaly problems, some studies, such as the one conducted by Porto e Memória (2019), restrict the analysis period by suppressing the years that contain anomalies. Others use simple procedures in an attempt to mitigate anomalies, such as repeating data or using averages to replace non-existent data. There are also those works that are silent on this issue. The importance of identifying and treating anomalies in time series is emphasized by Refaat e Hadi (2018) as an essential mechanism to increase the reliability of the analysis and to describe more accurately the phenomenon under study.

Therefore, in general, the analysis of time series of innovation indicators of a NIS can generate misleading conclusions about the behavior of a country, if an efficient and effective method of identifying and correcting anomalies is not adopted.

3 Anomalies in time series

In statistics, an anomaly, or *outlier*, , can be defined as an observation that deviates greatly from the others, causing suspicion as to how it was generated (HAWKINS, 1980). In other words, an anomaly represents a nonconformity with respect to an expected behavior, and is considered an exception (CHANDOLA; BANERJEE; KUMAR, 2009). Anomaly detection has been studied in a variety of applications, such as intrusion detection in *cyber* defense, credit card fraud detection, or fraudulent accounting in industry (BLÁZQUEZ-GARCÍA et al., 2021; GUPTA et al., 2014). Many of these studies are based on time series analysis (GUPTA et al., 2014).

Some methods for anomaly analysis in time series have been proposed, aiming, for example, at model training according to anomaly class, threshold optimization to improve anomaly detection, or time series prediction based on *deep-learning* – (BUDA; CAGLAYAN; ASSEM, 2018). However, the techniques, their parameters, and performances obtained depend essentially on the application, and are therefore difficult to generalize to a diverse range of problems (BLÁZQUEZ-GARCÍA et al., 2021).

4 Public policies and the incrementalism of innovation

Given the large number of unknown variables that influence or are influenced by public policy, policy makers often take conservative positions when making decisions about spending, budgeting, taxes, and other social factors (AINSWORTH; HALL, 2011; CARDOSO JÚNIOR; CASTRO, 2016; WILDAVSKY, 1966). As a consequence, public policies hardly make abrupt changes in the national reality (MICALE, 1990). They usually produce effects or results slowly and gradually, as suggested by the theory of incrementalism (LINDBLOM, 1959). Incrementalism, in this context, is equivalent to marginal changes that occur in small steps, continuing the patterns of thought and modus operandi already accepted by society (BRAYBROOKE; LINDBLOM, 1970; TEIXEIRA; MISSIO, 2011; WILDAVSKY, 1966).

In the field of technological innovation, incremental innovations, which in essence produce small changes, are more frequent than radical and disruptive ones (DOSI, 1982; FREEMAN; SOETE, 1997; JANGER et al., 2017; LUNDVALL, 2010). In many cases, radical innovations can jeopardize the return on investment of technologies that are widespread and accepted in the market, causing large companies to adopt conservative stances, to the detriment of the launching of novelties that might harm the products or services being comercialized. This trend, therefore, has led to a greater occurrence of incremental rather than radical innovations in various industries (JANGER et al., 2017).

Additionally, the incremental condition of innovation tends to be more intense in emerging countries, whose technology-based companies usually start their business from technologies acquired from foreign companies (HOBDAY, 1997; KIM, 2005). In these countries, these companies often adopt innovation techniques by imitation, do not master critical technologies, and engage in a gradual and increasing process of learning and accumulation of technological capabilities (FIGUEIREDO, 2004; KIM, 2005).

It is worth noting that even when radical innovations occur in the business environment, their signs manifest themselves early and progressively, and can be captured by the various variables of a NIS, such as those related to the indication of investments in R&D, scientific publications, patents, creation of startups, etc (MAZZUCATO, 2014).

Therefore, radical innovations are the result of actions that take place over time, from the emergence of ideas and inventions that develop, traveling a long way until they become successful products and services (TROTT, 2008). The "radical" effect is perceived from the market's point of view, where both the end user and the companies promoting these innovations are faced with changes in habits, competencies, capabilities and procedures (AFUAH; BAHRAM, 1995). Every innovation considered radical to an entity that receives it, such as the final consumer or a large integrating company, results from a laborious process of incremental innovation undertaken by the entity that provided it, such as component supplier companies (AFUAH; BAHRAM, 1995). Innovation, therefore, can be considered as a phenomenon that occurs in modern society, whose processes happen gradually and cumulatively, and may even arise from combinations of pre-existing possibilities and components, that is, future innovations are always dependent on the past (LUNDVALL, 2010).

In this conjuncture, radical innovations, important in the business context for its reflexes on the increase of productivity and competitiveness of the companies (AFUAH; BAHRAM, 1995; MAINE; THOMAS; UTTERBACK, 2014; SCHUMPETER, 1961), do not necessarily cause abrupt changes in a NIS (NIOSI et al., 1993). According to evolutionary theory (NELSON; WINTER, 1982), dominant design and technological regimes evolve in incremental cycles, causing nationwide systemic changes to occur slowly.

Given all the above, it is reasonable to admit that reliable NIS indicators do not experience abrupt changes over time. In this paper, the **Incrementalism of Innovation** is a concept that refers to the process in which the signals or effects of incremental and radical innovations are captured progressively by innovation indicators implemented at the national level, such as those of the GII.

5 Methodology

Initially, from an exploratory approach, and based on the incrementalism of a country's innovation capability, the concept of anomalies was formalized. It is worth pointing out that exploratory studies are adequate when there is little known about the reality in question and the intention is to open a path for new research (YIN, 1994).

Secondly, based on bibliographic research, using scientific articles, and documentary research, using GII reports, an attempt was made to identify the frequency of occurrence of anomalies in GII data and the effects of these anomalies on NIS analyses. All these anomaly-generating factors were triangulated across the various documents collected, thus enhancing the internal validity of the research (RIEGE, 2003).

Third, adopting incrementalism and Gaussian modeling of GII's BVs as assumptions, and using statistical inference tools, a method for automatic anomaly detection was developed. It is worth mentioning that, at first glance, one might think that the simplest way to detect anomalies is to consult the GII reports themselves. However, this approach is laborious, inefficient, and ineffective. The GII works with a very large set of variables (on the order of 80) and collects data from about 200 countries, so manually analyzing all this data in detail to identify problems takes a lot of time. Additionally, data collection or processing problems are not often pointed out in the reports. Moreover, the mere identification of anomalies is not enough to infer about possible problems in the NIS analyses, because in some cases they have little influence on the BV values. The key point is to identify the main anomalies, in the sense of their impact on the countries' assessment, and to classify them according to specific categories in order to deal with them appropriately.

Fourth, the classification of anomalies is performed, with the support of the GII reports, according to two categories: methodological and inconsistencies. As methodological changes are considered changes in the calculation of the baseline variables, as well as the inclusion and exclusion of BV. It should be noted that despite improving the quality of the indicators and accommodating the improvements in the understanding of the innovation phenomenon, it was found that these modifications often cause disturbances in the time series, constituting sources of anomalies, from the perspective of incrementalism. Inconsistencies, on the other hand, include practical issues such as missing data and problems in data generation, collection, and processing.

Finally, analysis of the functioning of the proposed procedure was performed discussing its use in Brazil's Innovation Product indicators for the period from 2013 to 2019.

5.1 Método propuesto para detectar y clasificar anomalías

The time series of the GII baseline indicators, as previously discussed, may contain several anomalies capable of impairing the reliability of studies on a country's NIS. The concept of the incrementalism of innovation, explored in Section 4, suggests that mild variations of GII indicators occur in consecutive years. In this work, a methodology is proposed to identify data that deviate from this normal pattern, a condition understood as very significant variations in a short interval of time for phenomena that manifest themselves nationwide. To reduce subjectivism regarding the employment of incrementalism and to avoid a fruitless discussion aimed at quantifying the meaning of "very significant variations," the methodology employs hypothesis testing to identify the supposedly anomalous situations. In summary, in this paper, it is proposed to adopt probabilistic modeling to describe GII's BVs, and from this modeling, a statistical test is constructed to infer about the "normality" of the data disclosed in GII's reports.

The GII background variables infer about complex phenomena that result from the influence of many unknown factors. Considering that these factors are probabilistically modeled and that they combine to generate the physical phenomenon measured by the BV, one can resort to the classical Central Limit Theorem and admit as valid the assumption that these variables can be described by Gaussian distributions, whose statistical parameters (mean and variance) remain practically constant over time, due to the assumption of incrementalism. Therefore, the time series of the GII baseline variables can be defined as a sample function of a Gaussian stochastic process.

Considerando que existen N_{VB} baseline variables over J ayears, which are represented by X_{ij} , para $i = 1,2, ..., N_{VB}$ e $j = 1,2, ..., J$, where $j = 1$, is the index specifying the first year of the time series and y $j = J$ the last year. Let μ_{ij} and σ_{ij} , be, respectively, the mean and standard deviation of X_{ij} .

Therefore, the random variable Z_i for $i = 1,2, ..., N_{VB}$ is defined as follows:

$$Z_i = \sum_{j=1}^{J} X_{ij}^2 \quad \text{Eq. 1}$$

has a chi-square distribution with $GL = J-1$ degree of freedom.

The test variable S_i, associated with the i-th GII baseline variable X_i is defined as follows:

$$S_i = \sum_{j=1}^{J} \left[\frac{\left(X_{ij} - \mu_{ij}\right)^2}{\mu_{ij}} \right] \quad \text{para} \quad i = 1, 2, \cdots, N_{VB}. \quad \text{Eq. 2}$$

Adopting the premise of incrementalism, one can admit as insignificant eventual changes in the statistical parameters of the random variables that model the baseline indicators, especially when considering a time interval of a few years. Therefore, one can approximate the random variable S_i by:

$$S_i = \sum_{j=1}^{J} \left[\frac{\left(X_{ij} - \mu_i\right)^2}{\mu_i} \right] \quad \text{para} \;\; i = 1, 2, \cdots, N_{VB}. \quad \text{Eq. 3}$$

Estimating the mean from the time series data of the baseline indicators, Eq.3 can be obtained, in practice, as follows:

$$S_i = \sum_{j=1}^{J} \left[\frac{\left(X_{ij} - \hat{\mu}_i\right)^2}{\hat{\mu}_i} \right] \quad \text{para} \;\; i = 1, 2, \cdots, N_{VB}. \quad \text{Eq. 4}$$

Where $\hat{\mu}_i$ is an unbiased estimator of the mean of X_i, , obtained from the data made available in the GII reports for the years under analysis. In this context, S_i eexpressed by Equation 4, it can be well approximated by a chi-squared random variable.

Taking S_i cas the test statistic, a hypothesis test can be defined to verify if the observations of the *i*--th indicator follow a Chi-square distribution, a fact that can serve to infer about the normality of the data disclosed by GII, since this statistical modeling was obtained considering restrictions imposed by the incrementalism premise.

The following definition of the null hypothesis of the Hypothesis Test is proposed: "there is no evidence of anomalies in the data". This means that the data are well behaved, oscillating around the arithmetic mean of the values obtained for the years considered $\hat{\mu}_i$, sfollowing a Gaussian distribution, in which the test variable, under the assumption of normality, has a Chi-square distribution. Abrupt changes would be taken as an indication of the occurrence of the alternative hypothesis defined as "there is evidence of abnormality in the data disclosed by GII". This hypothesis test is supported by the perspective that it is unreasonable for innovation indicators at the national level to present abrupt variations. Again, this does not mean that the BV should not change over time, but that it should behave like a Gaussian random variable whose statistical parameters change incrementally over time.

Therefore, if the null hypothesis is true, S_i, the test statistic, follows a Chi-square distribution. The risk of this hypothesis being rejected erroneously (Type I error) is called the significance level, α , usually a value much smaller than 1. That is, when the hypothesis test indicates as being true the normality of the data, according to the definition presented here for this condition, there will be a $1-\alpha$ probability that this assertion represents the truth of the facts, with this value being as close to 100% as desirable, assigning an appropriate α.

Confirmation of the null hypothesis will occur when the observation is within the region of acceptance, or, similarly, outside the region of rejection. Since this is a one-sided test, these regions are delimited by a single critical value (cV) which serves as a reference for comparison purposes for the test variable. That is, the null hypothesis will be true when: $P(\chi^2_{GL} < cV) = 1-\alpha$, being χ^2_{GL} a chi-square variable with degree of freedom DF, in which cV is defined as the value of α. In the concrete case, the test is as follows: if $S_i < cV$, it is decided for the normality of the data; otherwise, for the occurrence of anomalies.

The hypothesis test presented here separates the baseline variables for a given country into two sets, those that show some kind of abnormality in the data for the years considered in the study and those that follow the normality pattern.

The next step in the method is to classify the type of anomaly from the baseline variables that are supposed to have abnormalities. This is done by reapplying the hypothesis test and using the GII reports.

Initially, the same statistical test is used to identify the years that caused the violation of normality, progressively suppressing data from the time series that presented abnormality and repeating the hypothesis test for the series with suppressed data until the null hypothesis is observed, indicating that the remaining time series data behave according to the expected pattern.

Subsequently, it is verified for the baseline variables and years considered anomalous the occurrence of methodological changes from the GII reports. If no methodological changes are identified, it is decided that there is inconsistency in the data.

Summarizing, the proposed method consists of the following steps:

1. Perform a hypothesis test to determine whether the baseline variables behave in a manner consistent with the theory of incrementalism.

2. Create the $\mathbb{A}$ set of baseline variables that have anomalous data.

3. For each baseline variable in the $\mathbb{A}$, set perform hypothesis testing to identify the years that made the baseline variable anomalous.

4. Create the $\mathbb{B}$ set, formed by the data of the base variables of the years considered anomalous.

5. For each element in the $\mathbb{B}$, set, classify the anomalies between methodological change or inconsistencies, with support from the GII reports.

6 Case study

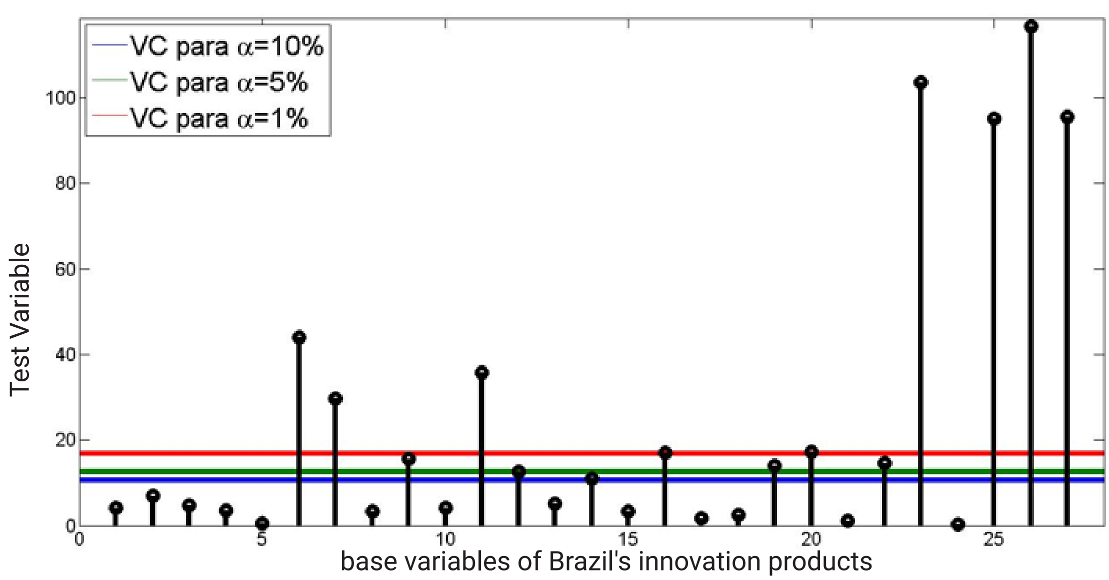
To apply the proposed method, Brazil's Innovation Product indicators from 2013 to 2019 will be used as a case study. Composed of the sub-pillars "Knowledge Products" and "Technology and Creative Products", the Innovation Products of Brazil, for the period considered, represents a good choice of compromise between space limitation for discussion of the results of the application of the method proposed here and the need to consider a relevant set of GII indicators capable of providing richness of situations involving anomalies.

Since the time series contains seven years ($J = 7$),), the Chi-square variables that model the Hypothesis Tests (HT) have six degrees of freedom ($GL = 6$). Annexx A presents a table with the critical values (CV) to be used in the hypothesis tests, both for the identification of BV with anomalies and the years in which they manifest themselves, in this case the degree of freedom of the Chi-square variable will be less than 6. The results discussed here were obtained for α , significance levels of 1%, 5% and 10%, for these values of α, when the test indicates that the data do not present anomalies, if the proposed modeling adequately captures the normality pattern in the data, there is, respectively, a 99%, 95% and 90% chance that the data do not present anomalies. Therefore, the analyst can be more rigorous in identifying abnormal data by adopting a small value for α,so that the smaller the value of this parameter the more conservative the test will be, as the probability of false alarm is reduced (that of classifying normal data as anomalous), while at the same time the probability of loss is increased (that is, the probability of not identifying anomalous data). In this way, if the modeling proves to be adherent to the real phenomenon, the analyst can count on an objective criterion to identify anomalies.

To obtain its Innovation Products indicators, GII uses the pillars Knowledge and Technology Products and Creative Products. Each one results from the average of three sub-pillars, which, in turn, are formed by the aggregate of three to five baseline variables, listed in Annex B.

The results of HT are shown in Chart 1, where the colored horizontal lines are the critical values as a function of α and the vertical lines are the values of the test variables of the 27 BVs of the GII Innovation Products for Brazil, indexed by i, as reported in Annex B. When the value of the test variable of the base variable exceeds the critical value, the statistical test indicates that the data of the BV under study do not follow the established pattern, which occurred with 14 of the 27 base variables for α igual al 10%, esta cantidad cae a 13 VB cuando se usa el valor de α equal to 5% and to 9 with α equal to 1%. This behavior of the hypothesis test is objective evidence that the modeling is coherent.

Chart 1– Values of the test variables of Innovation Products and CV as a function α



Source: The authors (2021).

Table 1 presents the list of baseline variables for Brazil whose data are considered anomalous as a function of the value of α.

Table 1 – Classification of the baseline variables according to the results of the statistical test.

α	i	Code	Variables de Base con Anomalías Conjunto $\mathbb{A}$
0,01	6 7 11 16 20 23 25 26 27	6.2.1 6.2.2 6.3.1 7.1.2 7.2.2 7.2.5 7.3.2 7.3.3 7.3.4	Growth rate of GDP per person engaged; New business density; Royalties and license fees receipts (% service exports); Madrid system trademark registrations by country of origin; National feature films produced; Creative goods exports Country-code top-level domains (ccTLDs) Wikipedia monthly edits Video uploads on YouTube
0,05	9 12 19 22	6.2.4 6.3.2 7.2.1 7.2.4	ISO 9001 quality certificates; High-tech exports; Audiovisual and related services exports; Printing and publishing output; e todas as obtidas com $\alpha = 0.01$.
0,10	14	6.3.4	Foreign direct investment net outflows; e todas as obtidas com $\alpha = 0.05$.

Source: The authors (2021).

The analysis that follows will be supported by the Annual Percentage Variation (APV) with respect to the average of the Baseline Variable i between years j e j+1 ($VPA_{i,j}$), defined as follows:

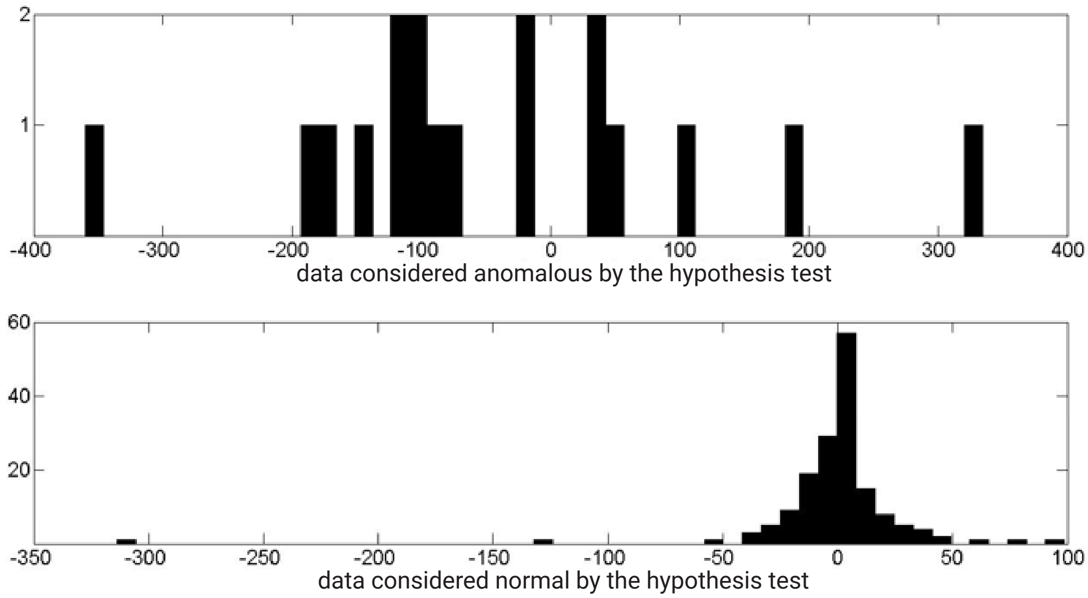
$$VPA_{i,j} = \frac{\left(X_{i,j+1} - X_{i,j}\right)}{\hat{\mu}_i} 100\% \quad \text{Eq. 5}$$

Chart 2 presents the histograms for the percentage variations from the mean of the base variables of the data considered anomalous and normal by the HT with $\alpha = 0{,}10$. It clearly shows that the Hypothesis Test correlates with the premise of incrementalism, since the aforementioned variations are small for the data considered normal and large for those detected as anomalous. Of the 189 data used to obtain this result (27 baseline variables from 2013 to 2017), 171 were found to be normal, of which in only 6 obtained a percentage variation from the mean of the baseline variable greater than or equal to 50%, which represents only 3.5% of the data. Whereas 14 of the 18 considered anomalous have a percentage variation greater than 50%, or 78% of the data.

Of course, detection procedures are subject to loss and false alarm errors. In this case, it is possible that some anomalies have been classified as normal and some normal data as anomalous, erroneously including both large percentage change values in the lower part of Chart 2 and small percentage change values in the upper part of Chart 2. However, regardless of the inevitable misconceptions of hypothesis testing (probability of loss and false alarm), it can certainly be said that the procedure separates the data into two groups according to the percentage variations from the means of the baseline variables in GII, with those with smaller variations being considered normal. This is evidence that the proposed test is able to separate the BVs that have abrupt variations from those with mild variations. .

It is worth reaffirming the consistency of the results presented in Table1 with respect to the value of α. As the value of this parameter decreases, the test becomes more conservative and therefore more sensitive to detect anomalies.

Chart 2 – Histogram of APV for anomalous (top) and normal (bottom) data.



Source: The authors (2021).

Chart 2 presents information related to the baseline variables classified as containing anomalies by the procedure proposed in this paper. This information covers not only the results of the hypothesis test, but also the anomaly classification obtained with support from the GII reports.

To identify the methodological changes that occurred from 2013 to 2019, the GII reports that present the baseline variables of Innovation Products were consulted. Assuming, preliminarily, that the proposed procedure correctly classifies the anomalies, when there is no change in the aforementioned reports, it is concluded that there are measurement inconsistencies (arising, for example, from data generation, collection and processing errors, and lack of data), and this information is detailed in Chart 2.

Methodological changes were verified in six of the fourteen BV containing anomalies (6.3.1, 6.3.2, 7.2.1, 7.2.4, 7.3.3, and 7.3.4). Of these, four produced important percentage variations and were correctly identified by the proposed procedure, including the year in which the changes occurred. The other two BVs with methodological changes (6.3.2 and 7.3.4) were not identified by the proposed procedure. However, in the case of Brazil, as seen in Chart 3, in the years in which methodological changes occurred (2014 in BW 6.3.2 and 2018 in BW 7.3.4) there were no significant changes in the BVs, so that there is no error in the method. On the contrary, it acted appropriately in pointing out the years in which the main changes occurred in these two BVs.

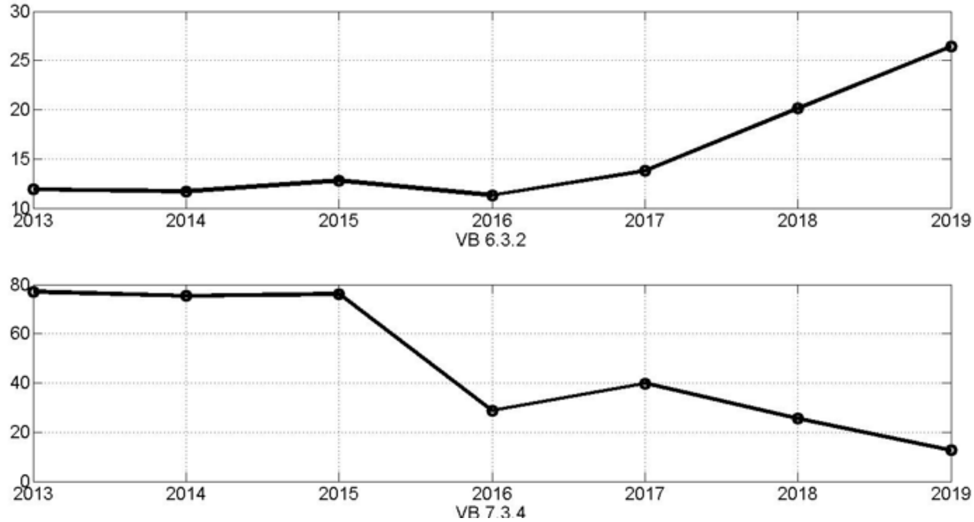
Table 2 – Baseline variables considered anomalous in the Hypothesis Test as a function of the value of α and classification of the anomaly according to the data from the GII reports.

α	Baseline Variable		Years		Type of anomaly Reports	$VPA_{i,j}$
	I	Code	TH	Reports		
0,01	6	6	2017	–	Inconsistency	101,1
	7	6.2.2	2017	–	Inconsistency	-142,8
0,05	9	6.2.4	2017	–	Inconsistency	-70,8*
0,01	11	6.3.1	–	2014	Methodological	0,6*
			2015	**2016**	**Methodological**	**-118,2***
			–	2019	Methodological	-13,1*
0,05	12	6.3.2	–	2014	Methodological	-1,3*
			2017	2017	Inconsistency	41,2
			2018	2018	Inconsistency	40,4
0,10	14	6.3.4	2014	–	Inconsistency	-25,1
0,01	16	7.1.2	2013-2015	–	Inconsistency	**
0,05	19	7.2.1	**2013**	**2014**	**Methodological**	**98,8***
0,01	20	7.2.2	2013	–	Inconsistency	-172,3
0,05	22	7.2.4	2013	–	Inconsistency	-112,7
			2017	**2018**	**Methodological**	**43,2***
0,01	23	7.2.5	2013	–	Inconsistency	-313,8
			2018	–	Inconsistency	-57,5
	25	7.3.2	2014	–	Inconsistency	-179,7
	26	7.3.3	**2016**	**2017**	**Methodological**	**334,28**
			2017	–	Inconsistency	-359,7
	27	7.3.4	2015	–	Inconsistency	-98,9
			–	2018	Methodological	-29,9*

Source: The authors (2021).

Notes:
* In methodological changes, the effect on the change in BV in principle manifests itself in the previous year's APV.
** Data were not provided for BV for the years 2013, 2014, and 2015. APV returned an infinite value.

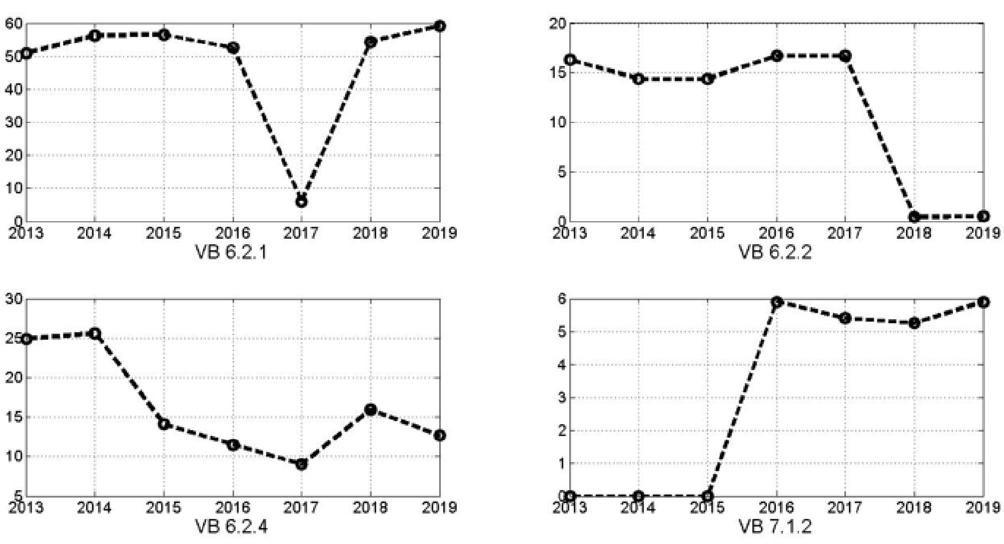
Chart 3 – Time series of anomalous BVs with methodological modifications not identified by TH.



Source: The authors (2021).

Table 3 presents eight BVs in which no methodological changes were found, so, according to the proposed procedure, inconsistencies are inferred. Such BV (6.2.1, 6.2.2, 6.2.4, 6.3.4, 7.1.2, 7.2.2, 7.2.5, 7.3.2) have high APV values. In Chart 4 the evolutions of four of these BVs are presented, in which it is evident that the inconsistencies are associated with significant variations in the indicators that need to be investigated in detail or even treated to correct errors in order to perform trend analyses reliably. In summary, the results summarized in Table 3 indicate that the method was successful in detecting anomalies.

Chart 4 – Time series of anomalous BVs without the occurrence of methodological changes.



Source: The authors (2021).

Tabla 3 –Informaciones obtenidas de los informes del GII para las Variables de Base que no presentaron anomalías en la Prueba de Hipótesis.

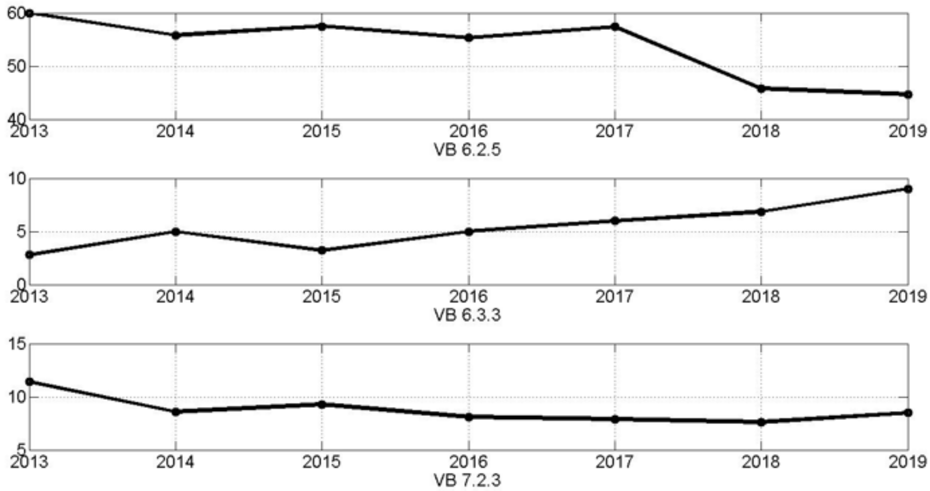
Baseline Variable		Years Reports	Type of anomaly Reports	Percentage Variation Anual* (%)
I	Code			
1	6.1.1	2013	None	80,6
2	6.1.2	2014	None	-125,3
3	6.1.3	2013	None	59,3
4	6.1.4	2017	None	-18,8
5	6.1.5	2014	None	-12,1
8	6.2.3	2013	None	30,6
10	6.2.5	2018	Methodological	-21,5
13	6.3.3	2014	Methodological	40,7
		2016	Methodological	33,3
		2019	Methodological	15,7
15	7.1.1	2013	None	40,1
17	7.1.3	2014	None	-12,2
18	7.1.4	2014	None	-15,2
21	7.2.3	2014	Methodological	-31,9
24	7.3.1	2013	None	-11,3

Source: The authors (2021).

Notes: *When no methodological changes are identified, the maximum APV of BV is presented.

Table 3 presents information from the 14 normal BVs, according to the procedure proposed here. Of these, three (6.2.5, 6.3.3 and 7.2.3) have undergone methodological changes, configuring, in principle, detection error of the statistical test. However, as shown in Chart 5, with the exception of BV 6.2.5, the other methodological changes did not cause significant changes in the indicators for Brazil, which is why it is not reasonable to consider that there was a mistake in the proposed procedure. On the other hand, the methodological change of BV 6.2.5 in 2018 seems to set a new plateau for the indicator, which should have been indicated by the proposed method.

Chart 5 – BV with anomalies that were not detected by the proposed method.

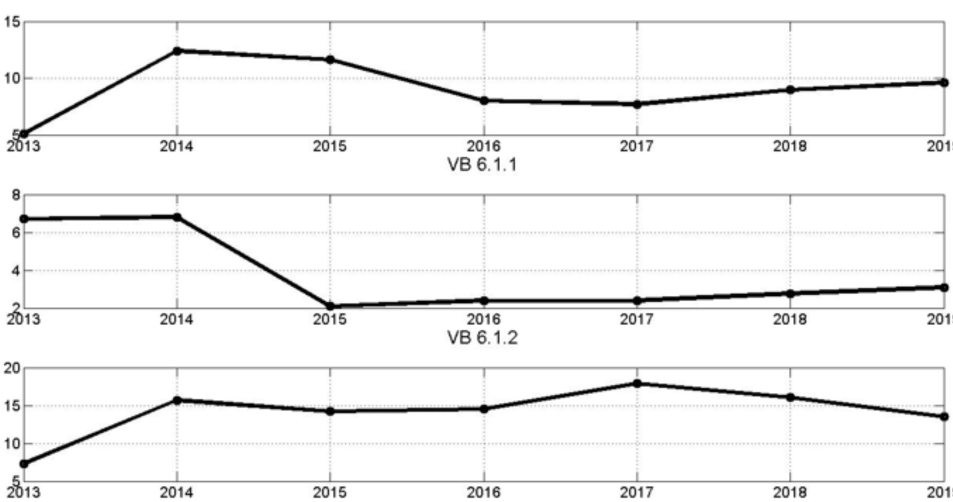


Source: The authors (2021).

Chart 6 shows normal BVs with high APV values. Among them is the variation in 2015 of VB 6.1.2, which can be characterized as a detection failure.

In summary, of all the cases analyzed, HT was wrong in two situations out of a total of 37 reported in Tables 2 and 3, setting a good performance for a hypothesis test, a 95% hit rate, consistent with the value of α used. This is a strong indication that the mathematical modeling performed on the premise of incrementalism and the adoption of a Gaussian distribution for the BVs and the proposed test, which was designed from approximations supported by the principle of incrementalism, are consistent and efficient in detecting anomalies.

Chart 6 - BV without anomalies with high APV values.



Source: The authors (2021).

7 Discussion

Starting from the premise of the incrementalism of the indicators of a NIS, which suggests that abrupt changes in a NIS are unlikely (MICALE, 1990; NIOSI et al., 1993), this paper presented the concept of anomalies in the indicators of GII and developed a technique to detect such anomalies and classify them as methodological or inconsistencies. This technique was built on the usual understanding of anomaly coming from the classical statistical literature (BLÁZQUEZ-GARCÍA et al., 2021; BUDA; CAGLAYAN; ASSEM, 2018; GUPTA et al., 2014) as well as the expected behavior of incremental development of a country's innovation capability (MICALE, 1990; NIOSI et al., 1993).

It was evident from the literature review that many researches use GII time series as a means to analyze the capability of an NIS. It was also shown that, not rarely, the GII variables have anomalies that hinder and compromise the precision of trend analyses, bottleneck identification and the evaluation of NIS capability (ERCIŞ; ÜNALAN, 2016; FAGERBERG; SRHOLEC, 2008; KHEDHAOURIA; THURIK, 2017; MILENKOVIC et al., 2019; WANG; ZHAO, X.; ZHANG, 2016).

The analysis of the case study data allowed us to verify that the main factors generating anomalies in a time series of GII indicators are methodological changes, lack of data, and data with atypical values, the latter considered as inconsistencies. The method was constructed to detect these factors by identifying abrupt changes in GII's BVs without requiring the need to establish a subjective measure of some parameter to encode the concept of "abrupt changes." From the definition of Annual Percentage Variation (APV), it was shown that the method achieved satisfactory results, managing to separate the BVs with data containing small APV values from those with high APV values.

It was verified, empirically, that some methodological changes were not detected by the method, particularly when they did not cause significant variations in the baseline variables. On the other hand, all changes that sensitively affected the values of the variables were detected by the proposed method. Thus, from the perspective of incrementalism, in both cases the hypothesis test worked correctly.

Similarly, the analyses performed here clearly showed that anomaly detections in the absence of methodological changes manifested themselves in situations of missing data and data with values quite distinct from the others in the time series. This is evidence of the relevance of the premise of incrementalism in the context of NIS; the efficiency of the proposed method as a useful mechanism to implement this premise in practice; and the coherence of the approaches that were adopted in its deduction.

As a hypothesis test, the proposed procedure presented satisfactory results, since no Type I critical errors were identified, when the null hypothesis is true and the test indicates that it is false (in this case "there is no evidence of anomalous data" and the test indicates the presence of anomalies) and Type II, which occurs in the opposite situation, that is, when the test accepts the null hypothesis and the alternative hypothesis has in fact occurred (in this case the test states that there is no presence of anomalies when in fact they exist).

Thus, in the context of GII, anomalies can be considered as abrupt changes in the behavior of innovation indicators in a given time period that can be generated by several factors, such as lack of data, methodological changes, or measurement errors. These abrupt changes are identified by estimating the significance level, α. The methodology described in this study was tested for three values of this parameter that controls the sensitivity of the hypothesis test in detecting abrupt changes (α = 1%, 5% or 10%). However, it is up to the analyst to choose the most appropriate α values according to the analyzed phenomenon.

Therefore, by suggesting that innovation indicators do not evolve sharply in a national context, the proposed method highlights the concept of anomaly often referenced by *outliers* in GII reports. The definition proposed in this paper differs from the term *outlier* used in these reports (SAISANA; DOMÍNGUEZ-TORREIRO; VÉRTESY 2018), since many significant changes in the values of the baseline variables arise from methodological changes and cannot be interpreted as *outlier*s.

8 Conclusion

The results presented here for the case study considered show the importance of identifying and classifying GII anomalies, as they can be significant, occur frequently, and mislead experts who analyze these indicators, compromising the accuracy of conclusions about the NIS.

It was shown that, although valuable, the mere analysis of the reports, besides being laborious, is not able to adequately solve this problem, because the effects and intensity of the methodological changes on the basic variables are quite diverse. Moreover, some important inconsistencies cannot be identified with such a procedure.

These characteristics highlight the value of developing procedures capable of identifying anomalies, distinguishing between them, and classifying them, as their causes and effects are distinct and need to be adequately considered in studies of trends and NIS capability.

For practical reasons, the present study was limited to analyzing Brazil's innovation outputs for the period 2013 to 2019, putting the topic in the spotlight and contributing, particularly, to studies on evolutionary analysis of innovation indicators that do not shy away from the rigorous work of detecting and treating anomalies.

Future studies can consolidate the technique proposed here by using it with other GII indicators, countries and time bands. The influence of the significance level value α on the probabilities of loss and detection failures can be studied further and other anomaly detection techniques can be implemented and compared with the procedure proposed here.

Authorship and Collaborations

All The authors participated equally in the elaboration of the article.

References

AFUAH, A. N.; BAHRAM, N. The hypercube of innovation. **Research Policy**, [s. l.], v. 24, n. 1, p. 51-76, 1995. Available at: http://www.sciencedirect.com/science/article/pii/004873339300749J. Accessed on: 13 jul. 2015.

AINSWORTH, S. H.; HALL, T. E. **Abortion politics in Congress**: strategic incrementalism and policy change. [Cambridge]: Cambridge University Press, 2011.

AVELLAR, A. P.; BRITO, J. Capacitação inovativa, investimento e produtividade na indústria brasileira: evidências da diversidade intersetorial. **Economia e Sociedade**, Campinas, v. 21, n. 2, p. 301-343, dez. 2015. Available at: https://periodicos.sbu.unicamp.br/ojs/index.php/ecos/article/view/8642287. Accessed on: 30 mar. 2020.

BLÁZQUEZ-GARCÍA, A. et al. A review on *Outlier*/anomaly detection in time series data. **ACM Computing Surveys**, [s. l.], v. 54, n. 3, p. 1-33, June 2021.

BRASIL. Tribunal de Contas da União. **Relatório de Auditoria 017.220/2018-1**. Auditoria realizada para identificar atores, políticas, iniciativas e arranjos institucionais relativos ao tema "Inovação", bem como os fatores que podem estar contribuindo para o persistente baixo posicionamento do Brasil nos *ranking*s de inovação. Recorrente: Secretaria de Controle Externo do Desenvolvimento Econômico. Relatora: Ana Arraes, 29 de maio de 2019. Available at: https://pesquisa.apps.tcu.gov.br/#/documento/acordao-completo/1722020181. PROC/ /DTRELEVANCIA desc, NUMACORDAOINT desc/0/ ?uuid=966eb5e0-9859-11e9-95b8-2537453d60df. Accessed on: 18 nov. 2019.

BRAYBROOKE, D.; LINDBLOM, C. E. **A strategy of decision**: policy evaluation as a social process. [New York]: Free Press, 1970.

BUDA, T. S.; CAGLAYAN, B.; ASSEM, H. DeepAD: a generic framework based on deep learning for time series anomaly detection. In: PHUNG, D. et al. (ed.). **Advances in knowledge discovery and data mining**. [S. l.]: Springer, 2018. p. 577-588. (Lecture Notes in Computer Science, v. 10937 LNAI).

CARDOSO JÚNIOR, J. C.; CASTRO, J. A. Economia política das finanças sociais brasileiras no período 1995-2002. **Economia e Sociedade**, Campinas, v. 15, n. 1, p. 145-174, jna. 2016. Available at: https://periodicos.sbu.unicamp.br/ojs/index.php/ecos/article/view/8642924. Accessed on: 30 mar. 2020.

CHANDOLA, V.; BANERJEE, A.; KUMAR, V. Anomaly detection: a survey. **ACM Computing Surveys**, [s. l.], v. 14, n. 1, p. 1-22, July 2009. Available at: https://dl.acm.org/doi/abs/10.1145/1541880.1541882. Accessed on: 18 out. 2021.

CRESPO, N. F.; CRESPO, C. F. Global innovation index: Moving beyond the absolute value of *ranking* with a fuzzy-set analysis. **Journal of Business Research**, [s. l.], v. 69, n. 11, p. 5265-5271, Nov 2016. Available at: http://dx.doi.org/10.1016/j.jbusres.2016.04.123. Accessed on: 23 nov. 2021.

DOSI, G. Technological paradigms and technological trajectories. A suggested interpretation of the determinants and directions of technical change. **Research Policy**, [s. l.], v. 11, n. 3, p. 147-162, 1982.

DUTTA, S. et al. Global innovation index 2018: energizing the world with innovation. In: DUTTA, S.; LANVIN, B.; WUNSCH-VINCENT, S. (ed.). **Global innovation index 2018**: energizing the world with innovation. 11th ed. [Geneva]: Cornell University; INSEAD; WIPO, 2018. p. 3-54. Available at: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2018.pdf. Accessed on: 24 nov. 2021.

DUTTA, S.; LANVIN, B.; WUNSCH-VINCENT, S. (ed.). **The global innovation index 2017**: innovation feeding the world. 10th ed. [Geneva]: Cornell University; INSEAD; WIPO, 2017. Available at: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2017.pdf. Accessed on: 24 nov. 2021.

ERCIŞ, A.; ÜNALAN, M. Innovation: a comparative case study of Turkey and South Korea. **Procedia**: Social and Behavioral Sciences, [s. l.], v. 235, p. 701-708, Nov 2016.

FAGERBERG, J.; MOWERY, D. C.; VERSPAGEN, B. The evolution of Norway's national innovation system. **Science and Public Policy**, [Oxford], v. 36, n. 6, p. 431-444, July 2009. Available at: https://mpra.ub.uni-muenchen.de/19330/1/MPRA_paper_19330.pdf. Accessed on: 23 nov. 2021.

FAGERBERG, J.; SRHOLEC, M. National innovation systems, capabilities and economic development. **Research Policy**, [s. l.], v. 37, n. 9, p. 1417-1435, Oct 2008. Available at: https://www.sciencedirect.com/science/article/pii/S0048733308001431. Accessed on: 29 abr. 2019.

FAMALIKA, A.; SIHOMBING, P. R. Implementation of K-Means and K-Medians Clustering in Several Countries Based on Global Innovation Index (GII) 2018. **Advance Sustainable Science, Engineering and Technology**, [Semarang], v. 3, n. 1, p. 0210107, 30 Apr 2021. Available at: http://journal.upgris.ac.id/index.php/asset/article/view/8461. Accessed on: 13 out. 2021.

FIGUEIREDO, P. N. Aprendizagem tecnológica e inovação industrial em economias emergentes: uma breve contribuição para o desenho e implementação de estudos empíricos e estratégias no Brasil. **Revista Brasileira de Inovação**, Campinas, v. 3, n. 2, p. 323, jul./dez. 2004. Available at: https://periodicos.sbu.unicamp.br/ojs/index.php/rbi/article/view/8648901. Accessed on: 23 nov. 2021.

FRANCO, C.; OLIVEIRA, R. H. de. Inputs and outputs of innovation: analysis of the BRICS. **INMR - Innovation & Management Review**, São Paulo, v. 14, n. 1, p. 79-89, 2017. Available at: https://www.revistas.usp.br/rai/article/view/112678. Accessed on: 23 nov. 2021.

FREEMAN, C.; SOETE, L. **The economics of industrial innovation**. [Cambridge]: MIT Press, 1997.

GALDINO, J. F. Análise de desempenho dos insumos de inovação do Sistema Nacional de Inovação do Brasil. **Exacta**, São Paulo, v. 17, n. 2, p. 75-93, 24 Maio 2019a. Available at: https://periodicos.uninove.br/exacta/article/view/8125. Accessed on: 23 nov. 2021a.

GALDINO, J. F. Reflexos da Era do Conhecimento e da 4ª Revolução Industrial na Defesa. **Artigos Estratégicos**, Brasília, DF, v. 6, n. 1, p. 7-27, jan./jun. 2019b. Available at: http://ebrevistas.eb.mil.br/index.php/CEEExArE/article/view/2492. Accessed on: 23 nov. 2021b.

GALDINO, J. F. Sistema Nacional de Inovação do Brasil: uma análise baseada no índice global de inovação. **Coleção Meira Mattos**: revista das ciências militares, Rio de Janeiro, v. 12, n. 45, p. 129-144, set./dez. 2018. Available at: http://ebrevistas.eb.mil.br/index.php/RMM/article/view/1391/1526. Accessed on: 30 dez. 2018.

GOMES, E. G. M. As agências reguladoras independentes e o tribunal de contas da união: conflito de jurisdições? **Revista de Administração Pública**, Rio de Janeiro, v. 40, n. 4, p. 615-630, ago 2006. Available at: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0034-76122006000400006&lng=pt&tlng=pt. Accessed on: 21 nov. 2019.

GROENEWEGEN, J.; STEEN, M. V. der. The evolution of national innovation systems. **Journal of Economic Issues**, [London], v. 40, p. 277-285, June 2006.

GUPTA, M. et al. *Outlier* **detection for temporal data**. San Rafael, California: Morgan & Claypool, 2014. (Synthesis Lectures on Data Mining and Knowledge Discovery).

HAWKINS, D. M. **Identification of** ***outlier*****s**. [London]: Chapman & Hall, 1980.

HOBDAY, M. **Innovation in East Asia**: the challenge to Japan. [S. l.]: Edward Elgar, 1997.

JANGER, J. et al. The EU 2020 innovation indicator: A step forward in measuring innovation outputs and outcomes? **Research Policy**, [s. l.], v. 46, n. 1, p. 30-42, Feb 2017. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0048733316301597. Accessed on: 25 jul. 2019.

JANKOWSKA, B.; MATYSEK-JĘDRYCH, A.; MROCZEK-DĄBROWSKA, K. Efficiency of national innovation systems - Poland and Bulgaria in the context of the global innovation index. **Comparative Economic Reasearch**: Central and Eastern Europe, v. 20, n. 3, p. 77-94, Sep 2017.

KHEDHAOURIA, A.; THURIK, R. Configurational conditions of national innovation capability: a fuzzy set analysis approach. **Technological Forecasting and Social Change**, [s. l.], v. 120, p. 48-58, July 2017.

KIM, L. **Da imitação à inovação**: a dinâmica do aprendizado tecnológico da Coréia. Campinas: UNICAMP, 2005.

KONDO, E. K. Desarrollo de indicadores estratégicos en ciencia y tecnología: principales problemas. **ACIMED**, Ciudad de La Habana, v. 9, p. 29-34, 2001. Supl. 4. Available at: http://scielo.sld.cu/pdf/aci/v9s4/aci05100.pdf. Accessed on: 19 nov. 2019.

KOSE, C.; TOPÇU, U. C. Innovation measurement revisited comparison of three main measures. In: INTERNATIONAL SCIENTIFIC CONFERENCE ON ECONOMIC AND SOCIAL DEVELOPMENT, 18., 2016, Zagreb, Croatia. **Book of proceedings**. Zagreb: Varazdin Development and Entrepreneurship Agency; University North; Faculty of Management University of Warsaw, 2016. p. 245-253. Available at: https://www.academia.edu/31163303/Innovation_Measurement_Revisited_Comparison_Of_Three_Main_Measures. Accessed on: 29 abr. 2019.

LINDBLOM, C. E. The Science of "Muddling Through". **Public Administration Review**, [Hoboken], v. 19, n. 2, p. 79-88, 1959. Available at: https://www.jstor.org/stable/973677?origin=crossref. Accessed on: 25 jul. 2019.

LUNDVALL, B-Å. Innovation system research and policy where it came from and where it might go. [S. l.: s. n.], 2007. Paper to be presented at CAS Seminar, Oslo, December 4, 2007. Available at: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.502.1643&rep=rep1&type=pdf. Accessed on: 24 nov. 2021.

LUNDVALL, B-Å. (ed.). **National systems of innovation**: toward a theory of innovation and interactive learning. [London]: Anthem Press, 2010. Available at: https://www.jstor.org/stable/j.ctt1gxp7cs. Accessed on: 26 jul. 2019.

MAINE, E.; THOMAS, V. J.; UTTERBACK, J. Radical innovation from the confluence of technologies: innovation management strategies for the emerging nanobiotechnology industry. **Journal of Engineering and Technology Management - JET-M**, [s. l.], v. 32, p. 1-25, Apr/June 2014.

MAZZUCATO, Mariana. **O Estado empreendedor**: desmascarando o mito do setor público vs. o setor privado. São Paulo: Portifolio-Penguin, 2014.

MICALE, L. M. **Policy change as innovation and incrementalism**: the case of Plan 6 cost-sharing. Tucson: The University of Arizona, 1990.

MILENKOVIC, N. et al. The correlation and interaction of the sustainability and global innovation in transition countries. **Applied Ecology and Environmental Research**, Budapest, v. 17, n. 2, p. 1499-1516, 2019. Available at: http://epa.oszk.hu/02500/02583/00058/pdf/EPA02583_applied_ecology_2019_02_14991516.pdf. Accessed on: 24 nov. 2021.

NELSON, R. R.; WINTER, S. G. **An evolutionary theory of economic change**. [Cambridge, MA; London]: Belknap Press of Harvard University Press, 1982.

NIOSI, J. et al. National systems of innovation: in search of a workable concept. **Technology in Society**, [s. l.], v. 15, n. 2, p. 207-227, 1993. Available at: http://linkinghub.elsevier.com/retrieve/pii/0160791X93900037. Accessed on: 23 nov. 2021.

PORTO, G. S.; MEMÓRIA, C. V. Incentivos para inovação tecnológica: um estudo da política pública de renúncia fiscal no Brasil. **Revista de Administração Pública**, São Paulo, v. 53, n. 3, p. 520-541, maio/jun. 2019. Available at: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0034-76122019000300520&tlng=pt. Accessed on: 21 nov. 2019.

RAGIN, C. C. **What is Qualitative Comparative Analysis (QCA)?**. Oxford: Oxford University, 2008. Economic and Social Research Council's Research Methods Festival, Saint Catherine's College, Oxford University. Available at: http://eprints.ncrm.ac.uk/250/1/What_is_QCA.pdf. Accessed on: 23 nov. 2021.

REFAAT, E.; HADI, A. Constructing composite indices. **International Journal of Sociology and Social Policy**, Bingley, UK, v. 38, n. 1-2, p. 58-86, 2018. Available at: http://www.emeraldinsight.com/doi/10.1108/IJSSP-12-2016-0135. Accessed on: 1 ago. 2019.

RIEGE, A. M. Validity and reliability tests in case study research: a literature review with "hands-on" applications for each research phase. **Qualitative Market Research**: an International Journal, Bingley, UK, v. 6, n. 2, p. 75-86, 2003. Available at: http://www.emeraldinsight.com/doi/10.1108/13522750310470055. Accessed on: 23 nov. 2021.

SAISANA, M.; DOMÍNGUEZ-TORREIRO, M.; VÉRTESY, D. Annex 3: Joint research centre statistical audit of the 2018 global innovation index. In: DUTTA, S.; LANVIN, B.; WUNSCH-VINCENT, S. (ed.). **Global innovation index 2018**: energizing the world with innovation. 11th ed. [Geneva]: Cornell University; INSEAD; WIPO, 2018. p. 71-87. Available at: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2018.pdf. Accessed on: 24 nov. 2021.

SANTOS, E. C. do C. Papel do Estado para o desenvolvimento do SNI: lições das economias avançadas e de industrialização recente. **Economia e Sociedade**, Campinas, v. 23, n. 2 (51), p. 433-464, ago. 2014. Available at: https://periodicos.sbu.unicamp.br/ojs/index.php/ecos/article/view/8642149/9641. Accessed on: 23 nov. 2021.

SCHUMPETER, J. A. **The theory of economic development**: an inquiry into profits, capital, credit, interest, and the business cycle. Translated by Redvers Opie. Cambridge, MA: Harvard University Press, 1961.

SCHONS, D. L.; PRADO FILHO, H. V.; GALDINO, J. F. Politica Nacional de Inovação: uma questão de crescimento econômico, desenvolvimento e soberania nacional. **Coleção Meira Mattos**: revista das ciências militares, Rio de Janeiro, v. 14, n. 49, p. 27-50, jan./abr. 2020. Available at: http://ebrevistas.eb.mil.br/RMM/article/view/3063/2679. Accessed on: 23 nov. 2021.

SCHONS, D. L.; PRADO FILHO, H. V.; GALDINO, J. F. **Estudo comparado de sistemas setoriais de inovação**: petróleo e gás, agronegócio e Exército. In: ESTUDOS de defesa: inovação, estratégia e desenvolvimento industrial. Rio de Janeiro: Ed. FGV, 2021 (no prelo). p. 190-218.

SOGNER, K. Slow Growth and revolutionary change: the norwegian IT Industry enters the global age, 1970-2005. In: FAGERBERG; J.; MOWERY, D.; VERSPAGEN, B. **Innovation, path dependency, and policy**: the Norwegian case. Oxford: Oxford University Press, 2009. p. 264-294. Available at: http://www.oxfordscholarship.com/view/10.1093/acprof:oso/9780199551552.001.0001/acprof-9780199551552-chapter-10. Accessed on: 8 jul. 2019.

TEIXEIRA, A. M.; MISSIO, F. J. O "novo" consenso macroeconômico e alguns insights da crítica heterodoxa. **Economia e Sociedade**, Campinas, v. 20, n. 2, p. 723-297, ago. 2011 Available at: https://periodicos.sbu.unicamp.br/ojs/index.php/ecos/article/view/8642349. Accessed on: 30 mar. 2020.

TROTT, P. **Innovation management and new product development**. [Harlow]: Financial Times/Prentice Hall, 2008.

WANG, D; ZHAO, X.; ZHANG, Z. The time lags effects of innovation input on output in national innovation systems: the case of China. **Discrete Dynamics in Nature and Society**, London, v. 2016, p. 1-12, Sep 2016. Available at: https://www.hindawi.com/journals/ddns/2016/1963815/. Accessed on: 23 nov. 2021.

WILDAVSKY, A. The political economy of efficiency: cost-benefit analysis, systems analysis, and program budgeting. **Public Administration Review**, [Hoboken], v. 26, n. 4, p. 292-310,, Dec 1966. Available at: https://www.jstor.org/stable/973301?origin=crossref. Accessed on: 25 jul. 2019.

YIN, R. K. **Case study research**: design and methods. 2nd, rev. ed. Thousand Oaks: SAGE Publications, 1994.

ANNEX A - Critical Values of the Chi-Square Variable for Different Degrees of Freedom and $1-\alpha$.

GL	$1-\alpha$			
	0,9	**0,95**	**0,975**	**0,99**
1	2,71	3,84	5,02	6,64
2	4,61	5,99	7,38	9,21
3	6,25	7,81	9,35	11,3
4	7,78	9,49	11,1	13,3
5	9,24	11,1	12,8	15,1
6	10,6	12,6	14,4	16,8

ANNEX B - List of Pillars, Sub-Pillars, and Baseline Variables (BV) of Innovation Products. The BVs are labeled by the index i, first column of the Chart.

Index (*i*)	Code	Description
	6.	Knowledge and technology outputs
	6.1.	Knowledge creation
1	6.1.1.	National office resident patent applications
2	6.1.2.	Patent Cooperation Treaty resident applications
3	6.1.3.	National office resident utility model applications
4	6.1.4.	Scientific and technical publications
5	6.1.5.	Citable documents H index
	6.2.	Knowledge impact
6	6.2.1.	Growth rate of GDP per person engaged
7	6.2.2.	New business density
8	6.2.3.	Total computer software spending
9	6.2.4.	ISO 9001 quality certificates
10	6.2.5.	High-tech and medium-high-tech output
	6.3.	Knowledge diffusion
11	6.3.1.	Royalties and license fees receipts (% service exports)
12	6.3.2.	High-tech exports
13	6.3.3.	Communications, computer and information services exports, %
14	6.3.4.	Foreign direct investment net outflows
	7.	Creative outputs
	7.1.	Intangible assets

Index (*i*)	Code	Description
15	7.1.1.	National office resident trademark registrations
16	7.1.2.	Madrid system trademark registrations by country of origin
17	7.1.3.	ICTs and business model creation
18	7.1.4.	ICTs and organizational models creation
	7.2.	Creative goods and services
19	7.2.1.	Audiovisual and related services exports
20	7.2.2.	National feature films produced
21	7.2.3.	Daily newspapers circulation
22	7.2.4.	Printing and publishing output
23	7.2.5.	Creative goods exports
	7.3.	Online creativity
24	7.3.1.	Generic top-level domains (gTLDs)
25	7.3.2.	Country-code top-level domains (ccTLDs)
26	7.3.3.	Wikipedia monthly edits
27	7.3.4.	Video uploads on YouTube

ECEME