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Testing of Published Information on Greenhouse Gas Emissions.

Conformity Analysis with the Benford's Law Method

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Abstract

The issue of greenhouse gas emissions and climate change cannot be overlooked from the scope of concern essential to develop the financial audit profession and implicitly the activity of the financial auditor. Within its professional field, the analysis of data quality on these issues requires applying divers analytical review methods, which incorporates unique statistical or mathematical rules. One of these is the analytical review procedure based on testing compliance of data distribution with Benford's Law. We present a practical case for testing the verisimilitude of data represented by greenhouse gas emissions, based on the Eurostat database. We applied the Benford's Law method for the first four digits, and the results were tested for likelihood by statistical methods such as Chi-square test or the Kolmogorov-Smirnov test. Information on greenhouse gas emissions is the basis for specific environmental policy decisions, which can be considered at the micro- or macroeconomic level. If this information is affected by subjective influences, then economic decisions or environmental policies will also be affected. Therefore, the objective of this research to test the plausibility of published data on greenhouse gas emissions proves its usefulness in relation with the actions performed by the economic and social players towards a sustainable development of the economy.

Keywords: *financial audit, ISAE 3410, assurance missions, greenhouse gases, environmental policy, Benford's Law.*

JEL Classification: *C10, M41, M42, M48*

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1. Introduction

Performing his work, the financial auditor has the opportunity to accomplish new activities, such as the assurance mission on greenhouse gas (GHG) statements. This type of activity is peculiar to professional standard 3410 – *Assurance Engagements on Greenhouse Gas Statements*[1] (ISAE 3410). Due to the link between the emission of these gases and climate change, GHG is of particular importance, with direct consequences on the decision-making process represented by the buildout of environmental policies at a micro- or macroeconomic level. The decision-making process is based on the quality and plausibility of the data obtained, which must not be subjectively influenced. Within this context, professional audit services can provide real support to the analysis of GHG-related data through the use of specific procedures, such as Benford's Law (BL), which may channel the future activity of the profession towards global and exceptional topics such as climate change.

The purpose of this article is the analyses of the verisimilitude of statistical data on greenhouse gas emissions obtained from the database provided by the European Environment Agency (EEA), through the conformity analysis with the distribution presented by Benford's Law. The analyzed data refer to CO_2 emissions from industrial processes and the use of products by EU countries, during the period 2008 – 2017, due to mutual geographical influences and connections. This data expressed in physical terms are estimated and not directly measured, based on a general calculation model promoted by Eurostat. The objective is part of a broader approach aimed at assessing environmental assets, with application in the field of investments specific to reducing the impact of greenhouse gas emissions inside Romania.

[1] IFAC (2015), Handbook of International Quality Control, Auditing, Review, Other Assurance, and Related Services Pronouncements, 2015 Edition, Volume II. Bucharest, 2016. *CAFR*, ISAE 3410 – *Assurance Engagements on Greenhouse Gas Statements*, pp.238-327.

2. Literature review

The advantages of an independent assurance mission within the field of financial audit, on a reporting on GHG emissions, were identified by PricewaterhouseCoopers (2007), but also by Simnett et al. (2009). As part of the formal process of developing the ISAE 3410 standard, a preliminary study (Consultation Paper) was conducted in October 2009 (IFAC, 2009).

In the research-based literature that addresses the subject of the application of Benford's Law, there are explanations of the mathematical phenomenon that underlies BL[2]. In 2009 Fewster, recommends for statistical verification of the results obtained after the application of BL, the Pearson Chi-square test.

Within the assurance assignment that is the subject of ISAE 3410[3], the financial auditor can use a full range of available procedures, from analysis of implemented controls, confirmations, observation, analysis of estimates, use of sampling, but also analytical review procedures, such as the method based on Benford's Law. The results of environmental policies can be jeopardized if the data on which they are based is manipulated (Matthew et al., 2019), or subject to subjective influences.

Also, the academic literature[4] has commented that if the data underlying the buildout of environmental policies is not reliable, there is a possibility that these policies may be ineffective (Cole, Maddison and Zhang, 2019). The authors point out that one of the reasons why the data may not be reliable is that this information can be consciously distorted to present a positive image

[2] Fewster, R. M. (2009), A Simple Explanation of Benford's Law, *American Statistician*, 63(1), pp. 26–32. doi: 10.1198/tast.2009.0005.

[3] IFAC (2015), Handbook of International Quality Control, Auditing, Review, Other Assurance, and Related Services Pronouncements, 2015 Edition, Volume II. Bucharest, 2016. *CAFR*, ISAE 3410 – Assurance Engagements on Greenhouse Gas Statements, pp.238-327.

[4] Cole, M. A., Maddison, D. J. and Zhang, L. (2019), Testing the emission reduction claims of CDM projects using the Benford's Law, *Climatic Change*, doi: 10.1007/s10584-019-02593-5.

of the impact on the surrounding environment. The authors consider the fact that this topic is not very well presented in the literature on climate change or the issue of greenhouse gas emissions, and the authors propose a simple technique for examining data integrity using Benford's Law. The authors also examine several papers that have applied BL in projects related to this topic:

- Dumas and Devine (2002);
- Brown (2005);
- Zahran et al. (2014);
- Fu et al. (2014);
- Stoerk (2016);
- Beiglou et al. (2017).

The applicability of the BL[1] method can be found in other studies utilized to accounting data.

3. Methodology

The research approach was based on an extended documentation and analysis of the academic literature on non-financial statements, as well as the analysis of data on greenhouse gas emissions. In this qualitative analysis, we examined the level of development of the corporate reporting system regarding social responsibility, but also the existence of several attempts to test the plausibility of data relating to GHG. Obviously, this information on GHG emissions implies an extent of technical specialization that certainly requires the existence of multidisciplinary teams. But for plausibility analysis, there are analysis alternatives represented by analytical review procedures, such as the application of BL. The next step of our research approach was to identify a source of quantitative data, related to GHG emissions, in order to move to the application of a quantitative method of analysis of data related to GHG emissions. The purpose of this approach is represented by the intention to verify the possibility of analyzing specific information in the professional and academic environment in Romania. The data source was represented by the information obtained from the EEA website[2], in the section **Greenhouse gas emissions by source sector (source: EEA) [env_air_gge]**, the data was last updated on 24 February 2020. The data expressed in physical terms are estimated and not directly measured, based on a general calculation model presented by Eurostat.

We applied to these data extracted from the database, the BL procedure for the first 4 digits, separately for each position. The statistical obtained results were tested and interpreted using the Chi-square and Kolmogorov-Smirnov tests. Under this interpretation, we paid more attention to the Kolmogorov-Smirnov test.

4. Results and discussions

4.1. General Overview

Benford's Law[3] refers to the frequencies' distribution of the figures in different occurrence circumstances for numerical information in real-life data sources. Thus, the number 1 appears as the first digit in 30% of cases. The distribution probability decreases for higher figures. The occurrence frequency of the first digits is similar with the size of the intervals of a logarithmic scale. It was found that the results apply to a wide variety of data. The law of distribution applies to numbers written in base 10. The phenomenon can be generalized for the occurrence of digits of numbers expressed in different numbering bases. A collection of numbers respects the BL distribution if the first digit (d) comprised between 1 and 9 has a distribution frequency with a probability (1):

$$\text{Probability}(d) = \log_{10}(d + 1) - \log_{10}(d) = \log_{10}(1+1/d) \quad (1)$$

where:

$$\Sigma\text{Probability}(d) = 1 \quad (2)$$

The occurrence of the digits on the first positions of a number respects BL and has the distribution shown in **Table no. 1**, with the graphical representation in ***Figure no. 1***:

[1] Durtschi C, Hillison W, Pacini C. (2004), The effective use of Benford's Law to assist in detecting fraud in accounting data, *Journal Forensic Accounting* 5, 2004: pp. 17–34.

[2] http://appsso.eurostat.ec.europa.eu/nui/setupDownloads.do;

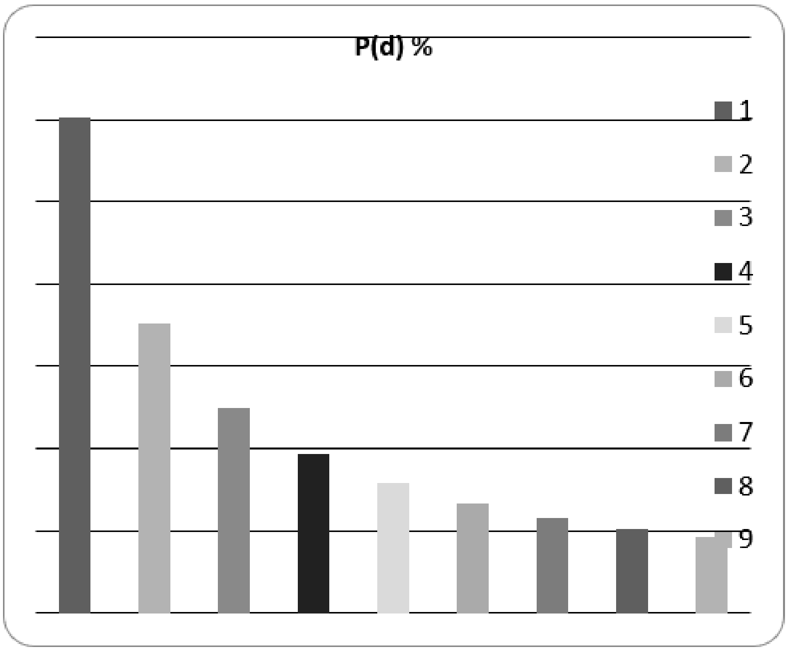
[3] Frank Bendford, The law of anomalous numbers, *Proceedings of the American Philosophical Society*, 1938, p. 78.

Table no. 1. Distribution of the first digit (Benford's Law)

d	Digit 1	Digit 2	Digit 3	Digit 4	Digit 5	Digit 6	Digit 7	Digit 8	Digit 9	Total
Probability(d)	30.1%	17.6%	12.5%	9.7%	7.9%	6.7%	5.8%	5.1%	4.6%	**100%**

Source: Author's work

Figure no. 1. Distribution of the first digit (Benford's Law)



Source: Author's work

The probability P(d) is directly related to the magnitude of the interval between **d** and **d+1** on a logarithmic scale, so it will respect the expected distribution of the mantissa (always positive decimal part of a logarithm) to the logarithm of that number, but not the number itself, being uniformly distributed from a probability point of view. The law is named after physicist Frank Benford[1]. Initially it was first mentioned by mathematician Simon Newcomb in 1881. The physicist Frank Benford verified this law on data from 20 different fields (20,229 observational data).

The probability P{D} that a number starts with the sequence {D}: F1, F2, F3, is (3):

$$P\{D\} = \log B(1+\frac{1}{D}) \quad (3)$$

The probability that the second significant (D2) digit of a number in the decimal system is k is presented in formula (4):

$$P_k = \sum_{i=1}^{9}(1 + \frac{1}{10i+k}),$$ k belongs to the integers beetween 0 and 9 (4)

The probability that the third significant (D3) digit of a number in the decimal system is k is (5):

$$P_k = \sum_{i=1}^{9}(1 + \frac{1}{100i+k}),$$ k belongs to the integers beetween 0 and 9 (5)

[1] Frank Bendford, The law of anomalous numbers, *Proceedings of the American Philosophical Society*, 1938, p. 78.

The probability that the last digit of a number in the decimal system is k (L1) is (6):

$P_k = \frac{1}{10}$, k belongs to the integers between 0 and 9 (6)

The BL model applies to data sets that are distributed in several orders of magnitude. Also, the model does not apply if we want to check the values in a list of invoices or payments between two limit values (for example, between 150,000 – 200,000 RON) or above a minimum value, or below the level of a maximum value.

The studies applied to specific accounting data have highlighted a set of criteria for the applicability of the BL[1]. Such criteria may be, for example, in the case of distributions where Benford's Law is applicable: large volumes of data, numbers resulting from mathematical calculations (**quantity** x **price**), or data resulting from actual trading operations (e.g. in the case of sales). The criteria that may attest to the impossibility of applying BL could be for accounting data: the situation in which the numbers are assigned (numbers of invoices, checks), where the numbers are influenced by subjective human decisions (prices of type 2.99), accounts with limitations maximum or minimum, or non-transaction accounts.

To statistically quantify the degree to which the observed data correlates with the mathematical model (*'goodness-of-fit'*) we may use several methods, among which we mention: Chi-square test, Kolmogorov-Smirnov 1, Kolmogorov-Smirnov 2, Kolmogorov-Smirnov 3, Kuiper test, Z test[2] (Farbaniec et al., 2011), **Table no. 2**.

Table no. 2. Statistical tests of likelihood (Benford's Law)

Test	Equation
Pearson Chi-square	$\chi^2 = \sum_{i=1}^{k} \frac{(n_i - np_i)^2}{np_i}$
Kolmogorov–Smirnov 1 (K-S1)	$KS1 = D\sqrt{\frac{n^2}{2n}}$ $D = max_i\lvert f_i - \hat{f}_i\rvert$ (i=1,…,k)
Kolmogorov–Smirnov 2 (K-S2)	$KS2 = D\sqrt{n}$ $D = max_i\lvert f_i - \hat{f}_i\rvert$ (i=1,…,k)
Kolmogorov–Smirnov 3 (K-S3)	$KS3 = V_N \cdot [\sqrt{N} + 0{,}155 + 0{,}24\, N^{-1/2}]$ (i=1,...,k)
Testul Kuiper	$V_N = D_N^+ + D_N^-$; $D_N^+ = sup_i\lvert f_i - \hat{f}_i\rvert$; $D_N^- = sup_i\lvert \hat{f}_i - f_i\rvert$; $N = \frac{n^2}{2n}$
Testul Z	$z_i = \frac{p_i - \hat{p}_i}{\sqrt{\hat{p}_i(1-\hat{p}_i)/n}}$

Source: Farbaniec, M. et al., 2011

To evaluate the degree of correlation between the two data sets we can use the Pearson correlation coefficient. The formula for the Pearson moment correlation coefficient ***r***, is (7):

$$r = \frac{\Sigma(x-\bar{x})(y-\bar{y})}{\sqrt{\Sigma(x-\bar{x})^2\ \Sigma(y-\bar{y})^2}} \quad (7)$$

where $\bar{x}$ and $\bar{y}$ are the averages for the samples.

4.2. Practical application

From the accessed EEA website[3], section **Greenhouse gas emissions by source sector (source: EEA) [env_air_gge]**, for the GHG likelihood test, we extracted a database in **csv** format with the following features:

[1] Durtschi C, Hillison W, Pacini C., The effective use of Benford's Law to assist in detecting fraud in accounting data, *Journal Forensic Accounting* 5, 2004: pp. 17–34.

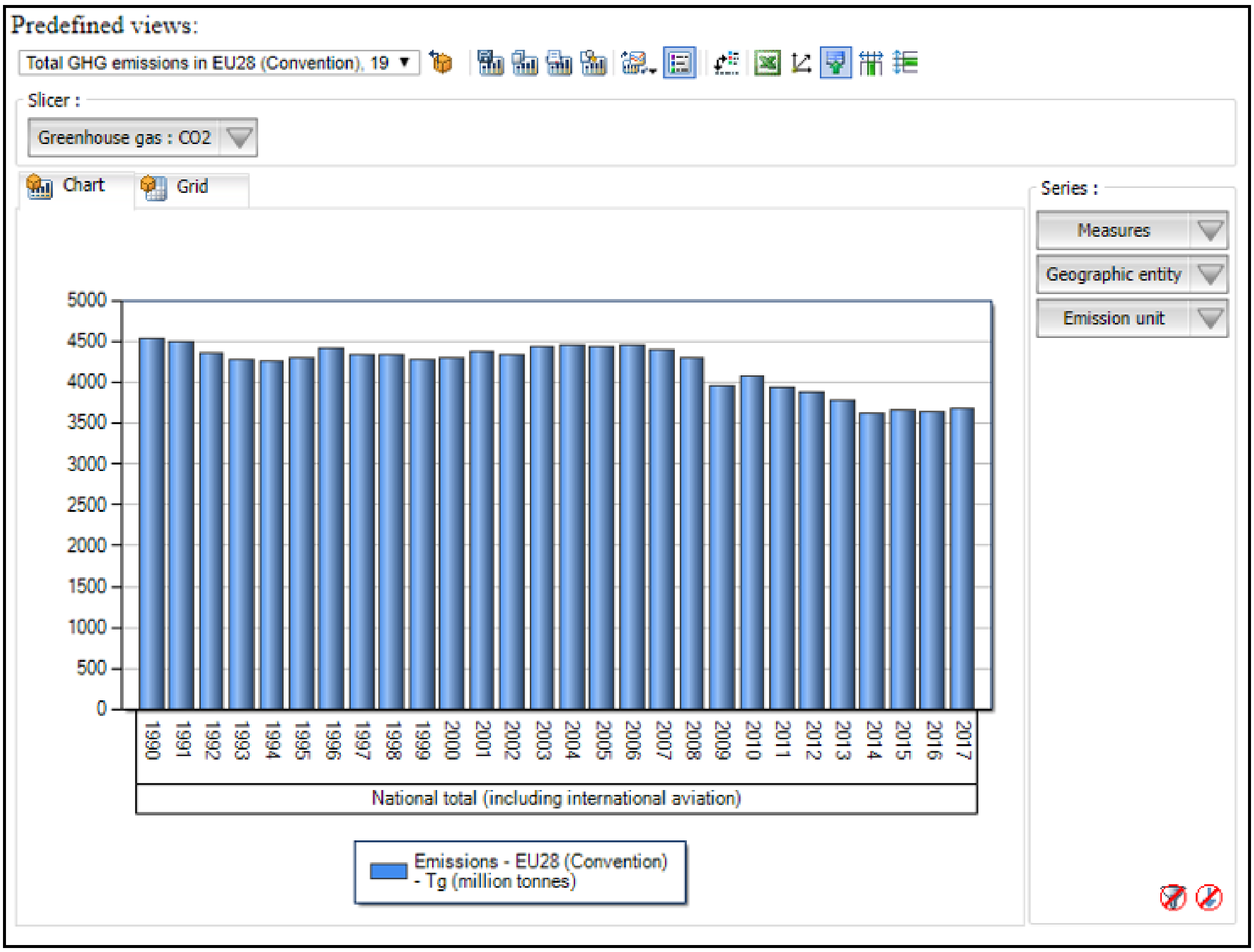
[2] Farbaniec, M. *et al.* (2011), Application of the first digit law in credibility evaluation of the financial accounting data based on particular cases, *10th International Congress on Internal Control, Internal Audit, Fraud and Anti-Corruption Issues, Kraków,* p. 27. Available at: http://benford.pl/documents/benford_pikw.pdf.

[3] http://appsso.eurostat.ec.europa.eu/nui/setupDownloads.do.

- Gaseous pollutant: CO_2, N_2O, CH_4, HFC, PFC, SF_6, NF_3 and aggregate value (GHG). Fluorinated gases and GHG aggregate value are expressed in CO_2 equivalent;
- Geopolitical entity (GEO): EU members, EFTA countries, candidate countries;
- Gas source sector (AIRESECT): sectors are classified according to the Common Reporting Format (CRF), aligned with UNFCCC reporting requirements;
- Time period: annual;
- Unit of measurement: thousands of tons and millions of tons.

The data downloaded in aggregate graphical form are presented in ***Figure no. 2***, the graphical representation is obtained in a predefined format made available to the public by the EEA.

Figure no. 2. Annual GHG emissions for EU28 between 1990 and 2017, reported by member countries to UNFCCC and EU Greenhouse Gas Monitoring



Source: https://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer

Following the processing of data on CO_2 emissions from industrial processes and the use of products by EU countries in the period 2008 – 2017, the application of the BL procedure for the first four digits resulted in the following data presented in **Table no. 3**.

Table no. 3. Probability test (Benford's Law) – practical application

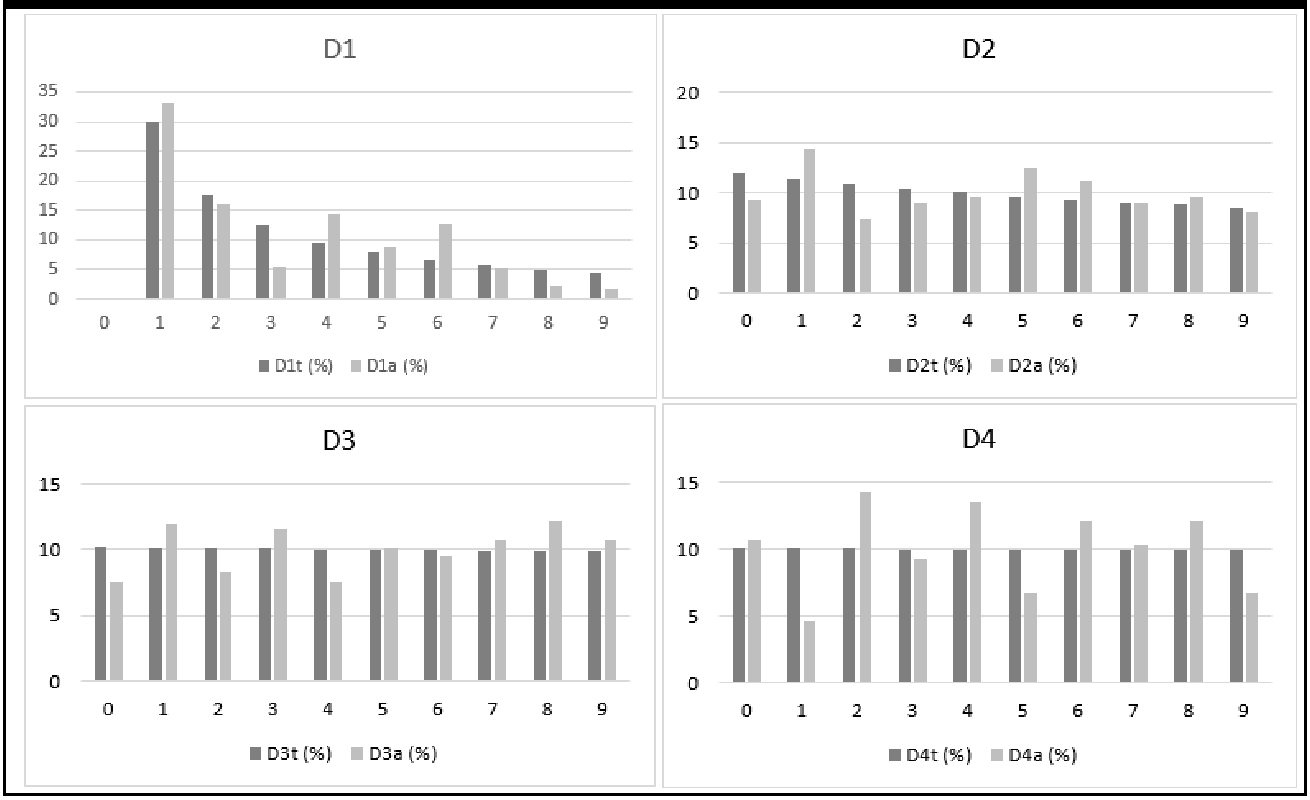
Digit	D1t (%)	Nb. events D1	D1a (%)	D2t (%)	Nb. events D2	D2a (%)	D3t (%)	Nb. events D3	D3a (%)	D4t (%)	Nb. events D4	D4a (%)
0				11.968	29	9.29	10.178	25	7.62	10.018	30	10.64
1	30.103	106	33.13	11.389	45	14.42	10.138	39	11.89	10.014	13	4.61
2	17.609	51	15.94	10.882	23	7.37	10.097	27	8.23	10.01	40	14.18
3	12.494	18	5.63	10.433	28	8.97	10.057	38	11.59	10.006	26	9.22
4	9.691	46	14.38	10.031	30	9.62	10.018	25	7.62	10.002	38	13.48
5	7.918	28	8.75	9.668	39	12.50	9.979	33	10.06	9.998	19	6.74
6	6.695	41	12.81	9.337	35	11.22	9.94	31	9.45	9.994	34	12.06
7	5.799	17	5.31	9.035	28	8.97	9.902	35	10.67	9.99	29	10.28
8	5.115	7	2.19	8.757	30	9.62	9.864	40	12.20	9.986	34	12.06
9	4.576	6	1.88	8.5	25	8.01	9.827	35	10.67	9.982	19	6.74
Total	100.000	320	100.00	100.000	312	100.00	100.000	328	100.00	100.000	282	100.00

Source: Author's work, based on the analyzed data

In **Table no. 3**, the parameters D1t, D2t, D3t and D4t represent the theoretical distribution of the first four digits, meanwhile D1a, D2a, D3a and D4a represent the distribution of the first four digits of the analyzed database.

The graphical representation of the BL distribution is shown in ***Figure no. 3***.

Figure no. 3. Graphical representation of BL test results



Source: Author's work, based on the analyzed data

By applying the Pearson Chi-square statistical test to assess the significance of statistical hypotheses we obtained a value close to zero, for the first digit, which leads us to the conclusion that we can reject the null hypothesis in this case, but is different from zero for the next three digits, with a significantly different value from zero for digit 3. The Pearson Chi-square test developed in 1900, is considered one of the tests underlying modern statistics. This is a non-parametric test, i.e. it is a test that does not specify details about the conditions of the population parameters from which a sample is extracted (**Table no. 4** – Statistical test (Pearson Chi-square)).

The assumptions of the test are the following:

- Null hypothesis (**H0**): States that there is no association between two population variables.
- Alternative hypothesis (**H1**): Proposes that the two variables are related to population.

Table no. 4. Statistical test (Pearson Chi-square)

Test CHI square D1			Test CHI square D2			Test CHI square D3			Test CHI square D4		
Digit 1 (D1)	Observed (D1)	Expected (D1)	Digit 2 (D2)	Observed (D2)	Expected (D2)	Digit 3 (D3)	Observed (D3)	Expected (D3)	Digit 4 (D4)	Observed (D4)	Expected (D4)
			0	29	34.67	0	25	36.44	0	30	31.33
1	106	35.56	1	45	34.67	1	39	36.44	1	13	31.33
2	51	35.56	2	23	34.67	2	27	36.44	2	40	31.33
3	18	35.56	3	28	34.67	3	38	36.44	3	26	31.33
4	46	35.56	4	30	34.67	4	25	36.44	4	38	31.33
5	28	35.56	5	39	34.67	5	33	36.44	5	19	31.33
6	41	35.56	6	35	34.67	6	31	36.44	6	34	31.33
7	17	35.56	7	28	34.67	7	35	36.44	7	29	31.33
8	7	35.56	8	30	34.67	8	40	36.44	8	34	31.33
9	6	35.56	9	25	34.67	9	35	36.44	9	19	31.33
	p-value	**0.0000**		**p-value**	**0.0800**		**p-value**	**0.4446**		**p-value**	0.0011

Source: Author's work, based on the analyzed data

We also calculated the Pearson correlation coefficient between the variable represented by the rate resulting from the data analysis and the calculated BL rate, and we obtained the following values of this coefficient: 0.908078, 0.2155485, (0.4022651), 0.0041272 related to D1, D2, D3 and D4, values that imply a high level of correlation for the first digit, but a low level of correlation for the next three digits.

For this reason, we applied the Kolmogorov-Smirnov likelihood test which is used to verify whether two samples come from the same distribution. If the first sample has **m** elements with the cumulative function observed by the distribution F(x) and the second sample has **n** elements with the cumulative function observed by the distribution G(x), then (8):

$$D_{m,n} = max_x |F(x) - G(x)| \qquad (8)$$

Null hypothesis H0: both samples come from a population with the same distribution. We reject the null hypothesis (at the level of significance α) if $D_{m,n} > D_{m,n,\alpha}$ where $D_{m,n,\alpha}$ is the critical value.
For m and n large enough (9):

$$D_{m,n,\alpha} = c(\alpha)\sqrt{\frac{m+n}{mn}} \qquad (9)$$

where c (α) = the inverse of the value of the Kolmogorov distribution at α and can be identified in the Kolmogorov-Smirnov distribution table.

The test results confirm that there is no significant difference between the two distributions (**Table no. 5**).

Table no. 5. Statistical test (goodness-of-fit) (Kolmogorov-Smirnov)

Test Kolmogorov-Smirnov D1			Test Kolmogorov-Smirnov D2			Test Kolmogorov-Smirnov D3			Test Kolmogorov-Smirnov D4		
	alpha	0.05		alpha	0.05		alpha	0.05		alpha	0.05
Cumm.% RE	Cumm.% BL	Diff.	Cumm.% RE	Cumm.% BL	Diff.	Cumm.% RE	Cumm.% BL	Diff.	Cumm.% RE	Cumm.% BL	Diff.
			9.29%	11.97%	2.67%	7.62%	10.18%	2.56%	10.64%	10.02%	0.62%
33.13%	30.10%	3.02%	23.72%	23.36%	0.36%	19.51%	20.32%	0.80%	15.25%	20.03%	4.78%
49.06%	47.71%	1.35%	31.09%	34.24%	3.15%	27.74%	30.41%	2.67%	29.43%	30.04%	0.61%
54.69%	60.21%	5.52%	40.06%	44.67%	4.61%	39.33%	40.47%	1.14%	38.65%	40.05%	1.40%
69.06%	69.90%	0.83%	49.68%	54.70%	5.02%	46.95%	50.49%	3.54%	52.13%	50.05%	2.08%
77.81%	77.82%	0.00%	62.18%	64.37%	2.19%	57.01%	60.47%	3.45%	58.87%	60.05%	1.18%
90.63%	84.51%	6.11%	73.40%	73.71%	0.31%	66.46%	70.41%	3.94%	70.92%	70.04%	0.88%
95.94%	90.31%	5.63%	82.37%	82.74%	0.37%	77.13%	80.31%	3.17%	81.21%	80.03%	1.17%
98.13%	95.42%	2.70%	91.99%	91.50%	0.49%	89.33%	90.17%	0.84%	93.26%	90.02%	3.24%
100.00%	100.00%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%
	D-stat	**0.061150**		**D-stat**	**0.050235**		**D-stat**	**0.039436**		**D-stat**	**0.047838**
	D-crit	**0.216221**		**D-crit**	**0.216562**		**D-crit**	**0.215895**		**D-crit**	**0.218009**
	Significant	**Not**		**Significant**	**Not**		**Significant**	**Not**		**Significant**	**Not**
D-stat < D-crit => diff. insignificant			D-stat < D-crit => diff. insignificant			D-stat < D-crit => diff. insignificant			D-stat < D-crit => diff. insignificant		

Source: Author's work, based on the analyzed data

5. Conclusions

Testing the likelihood of gas emissions data – expressed in physical terms without being measured but estimated, data published in Eurostat, based on the BL method, we obtained a result, which in turn was statistically tested by Pearson Chi-square methods and Kolmogorov-Smirnov. The result obtained strengthened our confidence in the raw data used. We base our confidence in the likelihood of the data, in particular on the interpretation of the statistical likelihood of the data following the application of the Kolmogorov-Smirnov test.

The importance of analyzing GHG emissions data is significant as of their effect on climate change, caused by global warming. This issue has entanglements for the decision-making process regarding environmental policies at macroeconomic level, but also for management decisions regarding environmental policies at a micro- or macroeconomic level. The impact refers to the fact that this issue involves answers that extend over long periods. Within this context, the economic analyzes based on these data depend to a large extent on their quality. The decision-making process is often triggered by the existence of risks, such as the risk of climate change, which can influence the social and economic danger.

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