FRAUD DETECTION BY TESTING THE CONFORMITY TO BENFORD'S LAW IN THE CASE OF WHOLESALE ENTERPRISES

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Abstract: The latest international crisis of the financial markets highlights the risks of instability, and the consequences of financial crime have a considerable effect on the performance of enterprises. The manipulation of selling prices or elements of financial statements even contribute to economic and social conflict in certain countries. The purpose of this study is to explore whether the conformity to Benford's law of forensic accounting data is sustainable in the case of wholesale trade enterprises in the examined (2009-2015) period and Hungarian region. Our research aims to test various elementary and advanced (goodness-of-fit) statistical techniques to assess the validity of the reported statements. Overall, after examining the deviations in reflected and expected frequencies we assert the non-conformity of this law in some cases. However, our motivation is not only to suggest applied recommendations to enhance accountability for entrepreneurships, but also to outline further research directions to improve the forensic fraud detection and better understanding of accountancy crimes for the management.

Key words: financial fraud, Benford's law, assessment of conformity, accounting and auditing

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Introduction

The latest crisis of international markets highlights the risks of financial instability that cannot be reduced without sufficient cooperation between banks and managers of enterprises in many countries (Obstfeld and Rogoff, 2009). The existing market imperfections have also indicated several difficulties for entrepreneurship related to sustainable development. However, the entrepreneurial sector, even in a recession, is less resistant to crime than other sectors all over world. Moral hazard is one of the crucial arguments of abuse during economic recessions. According to Stiglitz (1983), it is a possibility that SMEs will take less care to prevent an accident if they have insured against bankruptcies. However, the banking system offers protections i.e. facilities for emergency financial support to their clients, and allowances to

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control unwise risk taking by firms. Hence, appropriate supervision of enterprises and restrictions on their financial statements are necessary to limit the moral hazard resulting from deposit insurance and access to the lender of last resort. Otherwise, this lead SMEs to take out excessively risky loans and make inadequate provision for their next possible failure (Krugman, 2009).

Moreover, Akerlof and Romer (1994) have also demonstrated that failure to punish criminals creates incentives for more economic crimes and further damage to the economy in the future. Thus, if legal authorities seem to be manipulative, then trust and confidence in the whole economic system starts to erode (Freeman, 2012). However, moral hazard as a real option is freely given to an enterprise in order to enhance the likelihood of generating profits for the management by undertaking risk for the entire organization (Frunza, 2016). The manipulation of prices or elements of financial statements can even contribute to political disorder and social conflict in certain industries. Moreover, economies cannot recover if fraud is not prosecuted and if banks and managers feel that government or law enforcers will bail them out every time they get into trouble (Hoff and Stiglitz, 2005). This is one of the essential reasons to determine the processes account for these frauds. In this context, the increasing opportunity for financial crime highlights the need to have appropriate methods in place to detect abnormalities in markets.

According to the report of the Association of Certified Fraud Examiners (ACFE, 2016), wholesale trade and mining had the fewest fraud cases of any industries. However, this does not necessarily suggest that certain industries are more at risk of fraud than other sectors of economy, since this division is also prone to misreporting of financial results. The purpose of this study is to explore whether the conformity to Benford's law for accounting data is sustainable in the case of trade enterprises in the examined period. Our research aims to discuss various elementary and advanced statistical techniques that can be used parallel to check the validity of financial statements.

The rest of this paper organized as follows. Section II summarizes the conceptual framework of forensic fraud detection. Thus, section III explains various standard (first, second and first-two) digit test and advanced statistical goodness-of-fit tools to check the (non)conformity) of Benford's law. Then, in section IV, we will also present the results of our analyses, in the case of Hungarian wholesale trade firms. This research paper ends with some policy implications and conclusion (section V). However, our motivation is not only to suggest a feasible point of reference for policymakers to enhance better performance for entrepreneurships, but also to outline further research directions to detect accountancy frauds in this sectoral perspective.

The Conceptual Framework of Forensic Fraud Detection

Newcomb (1881) stated that all digits do not appear equally in terms of frequency, although he could not provide further evidence for this phenomenon in the real-world and his findings remained unnoticed for almost sixty years. Later, Benford

(1938) rediscovered this mathematical rule and it became known as Benford's law. Analyzing the digit frequencies of logarithmic book pages, he implied that the first few pages were used more often than pages later on. This implies the relatively higher frequency of first digits than those occurring later. The so-called first-digit-law, or significant digit law, confirms that more numbers start with the lower digits such as 1, 2 or 3 than higher ones. Essentially, this law is an effective tool to help check financial irregularities and intended data fraud.

Nevertheless, several empirical researches focusing on Benford's law in terms of accounting and auditing have been carried out in previous decades. Carslaw (1988), as a pioneer, carrying out complete analyses of forensic anomalies in income numbers for a sample of New-Zealand and US firms. Since then, several articles have been also published by Nigrini (2012) to check the validity of this law in assessing the quality of accounting statements. Later, Hill (1995) provided a formal mathematical proof for the law and demonstrated how it works in the stock market. Although the accounting data conforms Benford's predicted pattern in most of the empirical research (Alali and Romero, 2013), (Nigrini, 2015), (Van Caneghem, 2016), but there are certain circumstances when digital analysis is not suitable. Durtschi et al. (2000) also provided empirical evidence for Benford's law using accounting data, and found close conformity for the first digit of a chosen sample, they identified several conditions under which further analysis is required. Meanwhile, Benford's analysis is not always appropriate when the dataset is comprised of assigned numbers (invoices), the numbers are influenced by human thought, or where no transaction is recorded (thefts, kickbacks, contract rigging).

Data and Methodologies

The analysis is based primarily on the authors' composed dataset, which represents financial statements (Balance Sheets, P&L Statements) of 561 enterprises operating in the wholesale industries in the Northern Grate Plain region between 2009 and 2015. The Northern Great Plain (Észak-Alföld) area is one of the (NUTS 2) regions of Hungary. It is also part of the Great Plain and Northern (NUTS 1) regions and includes the counties of Hajdú-Bihar, Jász-Nagykun-Szolnok, and Szabolcs-Szatmár-Bereg, with a total area of 17.749 km^2 and a population of cc. 1.5 million inhabitants. Overall, we have an unbalanced panel data based on the annual financial statements of trade SMEs, with 3812 observations.

In order to assess the conformity of data, several basic and advanced tests can be used to analyze data manipulation, accountancy frauds and inefficiencies. One of the most commonly used empirical techniques for comparing actual data with expected Benford's series is through first, second and first-two digit tests. Here, a digit can refer to 1 to 9, or 10 to 99. First digits analysis is an initial test of sensibleness that is not intended to select audit samples. Generally, it is the first test to be performed during digital analysis of accounts. Second digits analysis is used as an additional test to establish whether the assumption of Benford's distribution is reasonable.

Meanwhile, the first-two digits analysis can be used for sample selection, but mostly in an indirect way to indicate which digit groups are 'overused' (Lolbert, 2007). In these approaches, the Z-statistic is an accurate test used to estimate whether the actual proportion of these digits differ significantly from expectations. As a 'thumb' rule, if Z-stats higher than the critical values of 1.96 at a 0.05 p-level indicate forensic frauds. Essentially, Z-statistic suffers from excessive statistical problems, i.e. it signs many significant differences for large datasets even if the differences are quite minor (Nigrini and Miller, 2008) . Hence, this test has become more sensitive to deviations as observations have increased, and is not feasible for use with real data.

In order to overcome this phenomenon the Mean Absolute Deviation (MAD) test is proposed, so as to ignore the effects of the number of records. It also takes into account the absolute value of the difference among proportions, regardless of whether the value is positive or negative. Although the higher the MAD, the larger the average difference will be, there are no objective critical scores for decision-making. Drake and Nigrini (2000) offered some guidelines to determine critical scores and ranges for testing conformity against Benford's law, based on their personal experience (Table 1).

Table 1. The critical values and conclusions for various MAD values
(based on Drake and Nigrini, 2000:150)

Digits	Range	Conformity
First Digit	0.000 to 0.006	Close
	0.006 to 0.012	Acceptable
	0.012 to 0.015	Marginally Acceptable
	Above 0.015	Nonconformity
Second Digit	0.000 to 0.008	Close
	0.008 to 0.010	Acceptable
	0.010 to 0.012	Marginally Acceptable
	Above 0.012	Nonconformity
First-Two Digits	0.0000 to 0.0012	Close
	0.0012 to 0.0018	Acceptable
	0.0018 to 0.0022	Marginally Acceptable
	Above 0.0022	Nonconformity

Although the mean absolute deviation test ignores N in its calculations, conformity decisions can differ widely for the first, second, and first-two-digit tests and there are no objective critical values offered a conservative approach to these tests. Namely, if the test statistics are higher than one of the critical values, the most pessimistic conclusion should be interpreted. In these cases, further advanced tests for large data sets are encouraged so as to clarify (non) conformity (Nigrini and

Miller, 2008). In our opinion, using only the MAD test seems not to be the best solution. In order to achieve detailed analysis, further statistical techniques are used to measure goodness-of fit (GOF), to assess if the data conforms to its null hypothesis. The listed GOF tests' null and alternative hypotheses given below are the following. *H0*: The data follows the specified distribution. In other words, the digit conforms to Benford's expected frequency. The alternative hypothesis *Ha*: the data does not follow the required distribution. At 0.05 p-level we will reject H0.
In this research, we included the following GOF tests. The Pearson χ^2 statistic (Pearson, 1900); the Kolmogorov-Smirnov D-statistic (Kolomonorgov, 1933); the Euclidean distance D-statistic (Cho and Gaines, 2007); the Chebyshev distance M-statistic (Leemis et al., 2000); the Freedman's modification of Watson's U-square statistic (Freedman, 1981); (Watson, 1961), the Joint Digit Test T^2 statistic of a Hotelling type test (Hotelling, 1931); and the Joenssen's J-statistic, as a Shapiro-Francia type correlation test (Shapiro and Francia, 1972).

Results of Testing Benford's Law Conformity

The earlier sections covered the theoretical background and the description of statistical tests used in a Benford analysis. In this section, we will look at the digit patterns of databases of financial statement numbers with applied MAD tests to ignore the size of the distribution. Table 2 below represents the test results of three accounting entities, i.e. Sales, Cost of goods sold (CGS) and Accounts receivables (AR) for the first, second and first-two digits between 2009 and 2015.
According to the first and second digit results compared to the critical MAD values in 2009 and 2013 for Sales, and a year later in 2010 and in 2014 for Accounts receivables, the conformity seems to be violated. This lagged phenomenon, which occurs because of the extended payment delays on receivables, especially in times of reduced sales, rapidly leads to a reduction in working capital in many firms. Thus, in the year 2009 and later, the effects of the financial crisis and its consequences were also felt in Hungary.

Table 2. The results of MAD tests in the case of Sales, Cost of goods sold (CGS) and Account receivables (AR) between 2009 and 2015

MAD Tests	**Years**						
Sales	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
First	0.0158	0.0085	0.0125	0.0127	0.0112	0.0087	0.0111
Second	0.0092	0.0089	0.0098	0.0118	0.0170	0.0071	0.0130
First-two	0.0033	0.0035	0.0034	0.0037	0.0041	0.0036	0.0038
CGS	2009	2010	2011	2012	2013	2014	2015
First	0.0094	0.0102	0.0133	0.0110	0.0118	0.0065	0.0140
Second	0.0124	0.0115	0.0098	0.0099	0.0115	0.0064	0.0120
First-two	0.0039	0.0033	0.0030	0.0031	0.0036	0.0029	0.0044

AR	2009	2010	2011	2012	2013	2014	2015
First	0.0058	0.0082	0.0058	0.0130	0.0129	0.0115	0.0091
Second	0.0112	0.0199	0.0099	0.0120	0.0119	0.0167	0.0150
First-two	0.0034	0.0041	0.0036	0.0037	0.0036	0.0042	0.0034

Although both of the first-two digits test results are higher than the offered and updated (Nigrini, 2012) 0.0022 critical value, this supports the belief that these numbers do not conform to Benford's law. In our opinion, this critical value is too strict in this sectoral approach. Thus, there is no clear consensus regarding the strong rejection (Lolbert, 2007). It is also possible that the conformity conclusions differ for three digit tests. At this stage, some additional statistical methodologies are warranted to clearly justify the (non)conformity.

In Appendix, see Tables A.1, A.2 and A.3, we also display a comparison of the theoretical and also the observed distributions. The digit patterns of accounting datasets, such as Sales, Cost of goods sold (CGS) and Accounts receivables (AR) are examined with the listed goodness-of-fit tests during the period between 2009 and 2015. These tests present a peak of non-conformity in the case of first and first-two digits at Sales in 2009 and 2013. In fact, during the recession, suspicions of manipulation by the first-two digits increased with CGS in 2009. Thus, the lagged 'contagion' effects of the crisis and low debt enforcement revealed by Account receivables appeared in 2010 and 2014. Overall, the deviation from expected and reflected frequencies failed to conform to Benford's law and we can claim that it is not sustainable for trade enterprises in these cases.

Conclusions

Well-performed entrepreneurships play a significant role in all economies and are important generators of employment and being essential for economic recovery. Restricted access to financial resources is one of the most pressing challenges for the growth of SMEs and have been intensified by the financial crises of recent decades. In these economic conditions, most entrepreneurs have suffered a drastic decrease in demand for goods and services and a tightening in creditworthiness, which disturb their cash flows. Moreover, the increased payment delays on receivables, together with exaggerated inventories has resulted in an absence of working capital and less liquidity. Additionally, reported accountancy fraud, defaults, insolvencies and bankruptcies are also typical and confirm the SMEs' increased inability to obtain short-term financing (OECD, 2009).

In Hungary, two-thirds of SMEs are financed typically by temporary bank loans. In the new financial conditions, the higher risk of bankruptcies has transformed the terms of bank loans provided to enterprises for their operating activities (Potori et al., 2011). It is also important to highlight that SMEs are generally more vulnerable and lose their value in times of crisis (Kiss, 2016). Even in normal economic periods, enterprises need specific governance policies and programs. Since the previous crisis, numerous anti-crisis packages have been introduced in order to sustain their stability and stimulate SMEs with, i.e. consumption packages, reduced taxation policies, credit enhancement with recapitalization of banks, and reduced payment delays for public procurement etc. (Dima et al., 2014). Governments are also responding generally to support sales and prevent the depletion of SMEs' working capital, to enhance their access to liquidity and to help them maintain their investment abilities. Thus, the greater challenges with worsening access to credit enforce SMEs to explore alternate sources of financing, such as the use of their reserves, self-financing and factoring. (OECD, 2015).

Our results, showing the unsustainability of Benford's law in the case of wholesale enterprises, highlight the uncertainty of manipulation in financial statements. This is consistent with the beliefs of Frunza (2016), as demonstrated in an application of LIBOR manipulation on the securities market. However, in Hungary, the New Hungary Venture Capital Program has been also designed to improve the financial status of Hungarian SMEs by providing early-stage equity financing (Becsky-Nagy, 2016). Meanwhile, Oláh (2014) demonstrated that in this region the self-employed have the worst business expectations, while confidence increases with firm size (Polereczki et al., 2016).

The limitations of our estimations need to be also emphasized, because these empirical findings were only able to demonstrate one aspect of accountancy fraud. Although other determinants may affect the conformity of Benford's law, the validity of our conclusions is limited by the bias caused by the exclusion of these variables. Moreover, we believe that a better understanding of fraud detection is a potentially important element in forensic analytics in the success of governance policies to resolve the negative outcomes of forthcoming financial crises. Hence, further research directions in this sectoral approach could be fruitful and are worth future exploration.

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Appendix

Table A.1. The results of goodness-of-fit tests in the case of Sales (2009 and 2015)

GOF Tests	Years						
First Digit	2009	2010	2011	2012	2013	2014	2015
K-S test	0.9396	0.6845	0.7230	0.9758	0.8474	0.4995	0.4729
p-value	0.1398	0.3907	0.3462	0.1143	0.2018	0.6604	0.7227
Chi-square	19.825	7.7562	10.717	8.6802	11.814	4.8372	7.2986
p-value	*0.0110*	0.4576	0.2182	0.3700	0.1597	0.7748	0.5048
Euclidean Distance	1.3597	0.7853	1.0554	1.2248	0.9343	0.6311	0.7549
p-value	*0.0404*	0.6088	0.2232	0.0912	0.3817	0.8450	0.6630
Chebyshev Distance	0.8044	0.4525	0.6201	0.9758	0.5260	0.3142	0.4024
p-value	0.1305	0.7047	0.3496	*0.0442*	0.5299	0.9274	0.7802
Freedman-Watson	0.2274	0.1035	0.2183	0.1709	0.1044	0.0574	0.039
p-value	*0.0178*	0.2070	*0.0241*	0.0614	0.2140	0.5347	0.7306
Joint Digits Test	19.825	7.7562	10.717	8.6802	11.814	4.8372	7.2986
p-value	*0.0110*	0.4576	0.2182	0.3700	0.1597	0.7748	0.5048
JP-Square Corr.	0.9394	0.9804	0.9653	0.9567	0.9729	0.8624	0.9707
p-value	*0.0147*	0.4674	0.1457	0.0749	0.2896	0.8624	0.4952
First-two Digits	2009	2010	2011	2012	2013	2014	2015
K-S test	0.9810	0.8697	0.7230	1.2124	0.8474	0.6293	0.5298
p-value	0.2237	0.3489	0.5528	0.0787	0.3706	0.7057	0.8653
Chi-square	92.788	86.224	80.89	102.83	121.35	85.943	68.738
p-value	0.3708	0.5636	0.7180	0.1500	*0.0129*	0.5721	0.9453
Euclidean Distance	0.9751	0.9968	0.9312	1.0798	1.2131	0.9516	0.8778
p-value	0.5373	0.4436	0.7239	0.1589	*0.0115*	0.6428	0.8904
Chebyshev Distance	0.3391	0.3207	0.2870	0.3240	0.4560	0.2395	0.3254
p-value	0.4801	0.5881	0.7660	0.5346	0.0972	0.9535	0.5770

Freedman-Watson	0.2468	0.1124	0.1739	0.1471	0.1110	0.0781	0.0489
p-value	*0.0116*	0.1868	0.0522	0.0872	0.1831	0.3710	0.6658
Joint Digits Test	92.788	86.224	80.89	102.830	121.35	85.943	68.738
p-value	0.3708	0.5636	0.7180	0.1500	*0.0129*	0.5721	0.9453
JP-Square Corr.	0.7541	0.7726	0.764	0.6884	0.6799	0.7523	0.7233
p-value	0.3136	0.4888	0.4303	*0.0471*	*0.0382*	0.4604	0.7465

Table A.2. The results of goodness-of-fit tests in the case of Cost of goods sold (CGF) (2009 and 2015)

GOF Tests				Years			
First Digit	2009	2010	2011	2012	2013	2014	2015
K-S test	0.6757	0.5225	0.5810	0.8806	0.9814	0.4638	1.1363
p-value	0.3965	0.6295	0.5399	0.1749	0.1145	0.7397	0.0708
Chi-square	6.2339	7.9907	14.875	10.573	9.2543	4.0903	15.075
p-value	0.6211	0.4344	0.0542	0.2271	0.3213	0.8489	0.0577
Euclidean Distance	0.8081	0.9668	1.1153	0.9026	0.9017	0.5632	1.238
p-value	0.5787	0.3378	0.1714	0.4298	0.4398	0.9063	0.0767
Chebyshev Distance	0.5288	0.9689	0.7313	0.5173	0.4811	0.3584	1.0747
p-value	0.5257	0.1992	0.2030	0.5508	0.6146	0.8773	0.0947
Freedman-Watson	0.0787	0.0757	0.1057	0.1599	0.0908	0.0329	0.1727
p-value	0.3552	0.3745	0.2086	0.0728	0.2692	0.7968	0.0613
Joint Digits Test	6.2339	7.9626	14.875	10.573	9.2543	4.0903	15.075
p-value	0.6211	0.4371	0.0542	0.2271	0.3213	0.8489	0.0577
JP-Square Corr.	0.9793	0.9689	0.9581	0.9732	0.9826	0.9904	0.9278
p-value	0.4418	0.1992	0.0811	0.2791	0.5558	0.8537	0.8351
First-two Digits	2009	2010	2011	2012	2013	2014	2015
K-S test	0.8214	0.6102	0.6414	0,9655	1,1988	0.5816	1.2691
p-value	0.4076	0.7458	0.6968	0,2399	0,0840	0.7903	0.0559
Chi-square	117.181	74.312	82.572	80,340	104,330	61.491	88.683
p-value	*0.0243*	0.8681	0.6713	0.7327	0.1276	0.9885	0.4895
Euclidean Distance	1.1478	0.9180	0.8928	0.9222	1.0151	0.7937	1.0083
p-value	*0.0477*	0.7740	0.8559	0.7604	0.3732	0.9890	0.3903
Chebyshev Distance	0.3325	0.3752	0.3157	0.3520	0.2888	0.2896	0.3161
p-value	0.5210	0.3112	0.6196	0.4287	0.7642	0.7678	0.6032
Freedman-Watson	0.1111	0.0855	0.1057	0.1270	0.0903	0.0314	0.1330
p-value	0.1853	0.3150	0.2086	0.1332	0.2979	0.8779	0.0544
Joint Digits Test	117.179	74.276	82.572	80.340	104.330	61.491	88.683

p-value	*0.0243*	0.8687	0.6713	0.7327	0.1276	0.9885	0.4895
JP-Square Corr.	0.7129	0.7866	0.7897	0.7931	0.7950	0.8422	0.7045
p-value	0.0963	0.6331	0.6692	0.6987	0.7114	0.9753	0.6441

Table A.3. The results of goodness-of-fit tests in the case of Accounts receivables (AR) (2009 and 2015)

GOF Tests	Years						
First Digit	2009	2010	2011	2012	2013	2014	2015
K-S test	0.3240	2.1551	0.2334	0.7004	0.6491	0.5743	0.4217
p-value	0.9242	*0.0001*	0.9850	0.3603	0.4329	0.5517	0.8001
Chi-square	0.3240	7.8139	2.3541	9.1357	8.4179	9.7452	3.4845
p-value	0.9242	0.4519	0.9682	0.3310	0.3937	0.2834	0.9004
Euclidean Distance	0.4929	0.3305	0.4712	0.9018	0.9197	1.0493	0.6377
p-value	0.9577	0.5384	0.9656	0.4278	0.3987	0.2305	0.8358
Chebyshev Distance	0.3182	0.5737	0.2532	0.5653	0.4452	0.7247	0.4217
p-value	0.9305	0.4247	0.9771	*0.4400*	0.7002	0.1993	0.7534
Freedman-Watson	0.0145	0.2834	0.02103.	0.0365	0.0866	0.0559	0.0233
p-value	0.9723	*0.0078*	0.9222	0.7599	0.3025	0.5451	0.9061
Joint Digits Test	2.8564	3.2984	2.3541	9.1357	8.4179	9.7452	3.4845
p-value	0.9430	0.9143	0.9682	0.3310	0.3937	0.2834	0.9004
JP-Square Corr.	0.9910	0.9921	0.9922	0.9796	0.9691	0.9604	0.9861
p-value	0.8957	0.9007	0.9255	0.5336	0.2606	0.1285	0.8713
First-two Digits	2009	2010	2011	2012	2013	2014	2015
K-S test	0.5997	2.1802	0.4480	0.8182	0.7725	0.8450	0.7190
p-value	0.7642	*0.0001*	0.9496	0.4112	0.4759	0.3749	0.5693
Chi-square	74.797	113.94	104.23	109,46	88.058	138.51	69.822
p-value	0.8591	*0.0386*	0.1289	0.0696	0.5083	*0.0006*	0.9338
Euclidean Distance	0.9609	1.1513	1.0868	1.1756	1.0312	1.2883	0.8847
p-value	0.6040	*0.0395*	0.1401	0.0235	0.3102	*0.0016*	0.8777
Chebyshev Distance	0.3780	0.3305	0.4193	0.4345	0.3951	0.67319,	0.3590
p-value	0.2917	0.5384	0.1646	0.1404	0.2509	*0.0027*	0.3866
Freedman-Watson	0.0402	0.4006	0.0271	0.0413	0.1035	0.0729	0.0323
p-value	0.7779	*0.0003*	0.9312	0.7609	0.2171	0.4072	0.8756
Joint Digits Test	74.797	109.07	104.23	109,46	88.058	138.51	69,822
p-value	0.8591	0.0731	0.1289	0.0696	0.5083	*0.0006*	0.9338
JP-Square Corr.	0.7709	0.7118	0.7224	0.7121	0.7255	0.6701	0.7773
p-value	0.6394	0.0887	0.2474	0.2141	0.2649	0.0513	0.9704

WYKRYWANIE NADUŻYĆ FINANSOWYCH PRZEZ BADANIE ZGODNOŚCI Z PRAWEM BENFORDA W PRZYPADKU PRZEDSIĘBIORSTW HANDLU HURTOWEGO

Streszczenie: Ostatni międzynarodowy kryzys na rynkach finansowych podkreśla ryzyko niestabilności, a konsekwencje przestępstw finansowych mają znaczny wpływ na wyniki przedsiębiorstw. Manipulowanie cenami sprzedaży lub elementami sprawozdań finansowych przyczyniają się nawet do konfliktów gospodarczych i społecznych w niektórych krajach. Celem niniejszego artykułu jest zbadanie, czy dostosowanie do prawa danych księgowych Benforda jest trwałe w przypadku przedsiębiorstw handlu hurtowego w badanym okresie (2009-2015) w regionie Węgier. Przeprowadzone badania mają na celu przetestowanie różnych elementarnych i zaawansowanych (odpowiednio dopasowanych) technik statystycznych w celu oceny wiarygodności zgłaszanych oświadczeń. Po zbadaniu odchyleń w odzwierciedlanych i oczekiwanych częstotliwościach, w niektórych przypadkach stwierdzono niezgodność z tym prawem. Jednak motywacją autorów jest nie tylko zasugerowanie stosowanych zaleceń w celu zwiększenia odpowiedzialności w zakresie przedsiębiorczości, ale także nakreślenie dalszych kierunków badań w celu poprawy wykrywania oszustw i lepszego zrozumienia przestępstw związanych z rachunkowością zarządczą.

Słowa kluczowe: oszustwa finansowe, prawo Benforda, ocena zgodności, rachunkowość i audyt

通过检测批发企业符合本福法律的欺诈侦查

摘要:金融市场最新的国际危机凸显了不稳定的风险，金融犯罪的后果对企业绩效有相当大的影响。销售价格或财务报表要素的操纵甚至对某些国家的经济和社会冲突有所贡献。本研究的目的是探讨本德福法律会计数据的符合性是否符合经审查的(2009-2015年)批发贸易企业和匈牙利地区的情况。我们的研究旨在测试各种初级和高级(适合度)统计技术，以评估报告语句的有效性。总体而言，在考察了反映频率和预期频率的偏差之后，我们认为在某些情况下这一法律不一致。但是，我们的动机不仅是提出应用性建议，以加强对创业的问责，而且还提出进一步的研究方向，以提高对司法鉴定的侦查和更好地理解管理会计犯罪。

关键词:金融诈骗，本福特法则，合格评估，会计和审计