

A CONTINUOUS AUDITING IMPLEMENTATION WITH BENFORD’S LAW
AND RELATIVE DISCREPANCIES TO AN SME IN TURKEY



ALİ CANDAN

BOĞAZİÇİ UNIVERSITY

2021

A CONTINUOUS AUDITING IMPLEMENTATION WITH BENFORD’S LAW
AND RELATIVE DISCREPANCIES TO AN SME IN TURKEY

Thesis submitted to the
Institute for Graduate Studies in Social Sciences
In partial fulfillment of the requirements for the degree of

Master of Arts

In

Management

by

Ali Candan

Boğaziçi University

2021

A Continuous Auditing Implementation with Benford's Law
and Relative Discrepancies to an SME in Turkey

The thesis of Ali Candan
has been approved by:

Assist. Prof. Ali Coşkun
(Thesis Advisor)

Assoc. Prof. Gözde Ünal

Assoc. Prof. Mustafa Canbolat
(External Member)

June 2021

DECLARATION OF ORIGINALITY

I, Ali Candan, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

Signature.....

Date

ABSTRACT

A Continuous Auditing Implementation With Benford's Law And Relative Discrepancies to an SME in Turkey

In this study, we analyze the proper use of Benford's Law in the technique of continuous auditing to determine the audit sample of a Small to Medium-Sized Enterprise (SME). Most other studies analyze corporate firms; however, we tested an SME with a relatively small data set. While testing, we determined the best technique, frequency, and data-set type to create an audit sample. We analyzed weekly and monthly time intervals. Also, we sought to answer the question of which dataset to analyze: the cumulative or non-cumulative one. To answer these questions, we benefited from Benford's analysis and relative discrepancies techniques. The results demonstrate that using the relative discrepancies technique with a weekly cumulative dataset is the best option in our case.

ÖZET

Türkiye’de bir KOBİ’ye Benford Yasası ve Göreceli Tutarsızlık ile

Sürekli Denetim Uygulaması

Bu çalışmada, bir KOBİ’ye denetim örnekleme oluşturmak için sürekli denetim bağlamında Benford Yasasının uygun kullanımı analiz edilmiştir. Sürekli denetim konsepti ile ilgili çalışmaların çoğunluğunda analizler kurumsal şirketler üzerine yapılmıştır. Ancak bu çalışma göreceli olarak daha küçük veri setine sahip olan bir KOBİ üzerine yapılmıştır. Analizler yapılırken denetim örnekleme oluşturmak için en iyi tekniğin, zaman sıklığının ve veri seti tipinin ne olduğuna karar verilmeye çalışılmıştır. Çalışmada haftalık ve aylık zaman sıklıklarında analizler yapılmıştır. Çalışmada cevap aranan bir diğer soru ise veri seti tipidir. Bu bağlamda kümülatif ve kümülatif olmayan veri setleri analiz edilmiştir. Tüm bu soruları cevaplayabilmek için benford analizi ve göreceli tutarsızlık tekniklerinden yararlanılmıştır. Çalışmanın sonucuna göre, haftalık ve kümülatif veri setini göreceli tutarsızlık tekniği ile analiz etmek bu senaryo için en iyi seçenektir.

ACKNOWLEDGMENTS

My sincere thanks to my thesis advisor, Assistant Professor Ali Coşkun, for his support and contributions. At every step, he provided guidance and improved the quality of the study.

Also, I owe gratitude to committee members Associate Professor Gözde Ünal and Associate Professor Mustafa Canbolat. They made me aware of the weak parts of this study and guided me on how to make it robust.

I also want to express how thankful I am for my supportive wife, and it is an honor to thank my mother and father who financed and freed me for the duration of my education.

This dissertation is dedicated to my wife Sıddıka, my mother Güzide,
my father Mustafa, my sister Büşra, and my little brother Ahmet.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION	1
CHAPTER 2: LITERATURE REVIEW	4
2.1 Auditing.....	4
2.2 Traditional auditing	5
2.3 Internal auditing	6
2.4 Continuous auditing	9
2.5 Benford's Law	15
2.6 Relative discrepancies	21
CHAPTER 3: RESEARCH QUESTION AND METHODOLOGY	23
3.1 The research problem	23
3.2 The purpose of the study	23
3.3 The research questions	23
3.4 Methodology	23
3.5 Data scope	24
3.6 Data analysis.....	26
CHAPTER 4: RESULTS	29
4.1 Benford analysis	29
4.2 Relative discrepancies	34
4.3 Comparison of the results.....	36
CHAPTER 5: CONCLUSION.....	37
5.1 Discussion of continuous auditing	37
5.2 Discussion of Benford's Law	38
5.3 Our implementation.....	39

5.4 Market benefit	40
5.5 Possible further studies.....	41
APPENDIX A: DIGIT DISTRIBUTION TABLES	43
APPENDIX B: RELATIVE DISCREPANCIES TEST RESULTS.....	55
APPENDIX C: R SCRIPT	61
REFERENCES.....	70



LIST OF APPENDIX TABLES

Table A1. Distribution Table (29.11.2020).....	43
Table A2. Distribution Table (06.12.2020).....	45
Table A3. Distribution Table (01.01.2021).....	47
Table A4. Discrepancies Table (29.11.2020).....	49
Table A5. Discrepancies Table (06.12.2021).....	51
Table A6. Discrepancies Table (01.01.2021).....	53



LIST OF FIGURES

Figure 1. Benford's observations (Benford,1938)	16
Figure 2. Frequency of digits in the first place (Benford,1938).....	17
Figure 3. Benford analysis dated 29.11.2020.....	29
Figure 4. Benford analysis dated 06.12.2020 cumulative.....	30
Figure 5. Benford analysis dated 06.12.2020 non-cumulative.....	31
Figure 6. Benford analysis dated 01.01.2021 cumulative.....	32
Figure 7. Benford analysis dated 01.01.2021 non-cumulative.....	33

CHAPTER 1

INTRODUCTION

Auditing is the process of examining an institution's financial records for compliance with regulations and laws. Also, in the course of the audit, financial records are checked for accuracy. Changes in business dynamics are inevitable, and accounting and auditing systems need to adapt to such changes. Technological developments profoundly affect and compel auditing systems to change.

Today's auditing systems involve excessive human interaction and are open to fraud. With the development of technology, new auditing tools and methods are coming into existence. These decrease dependence on human interaction in the auditing process and minimize opportunities for fraud. Continuous auditing is one of these innovative methods. There is no strict definition or methodology of continuous auditing. Its main purpose is to execute auditing on a more frequent basis, minimize human involvement, and maximize the number of records being audited. Moreover, it is possible to implement continuous auditing with traditional analyses that use probabilistic sampling, stratification, and non-probabilistic sampling to create audit samples. Benford's Law is one of the most common of these.

Benford's Law defines the unbiased distribution of first, second, and third digits of numbers in a data series. This means that a Benford's Law analysis can detect human manipulation of numbers. Benford's Law analysis has been widely used in auditing from the beginning, and the technique guides auditors in the process of determining suspicious records in the course of assembling an audit sample. However, Benford analysis is not suitable for a time series analysis, for which the relative

discrepancies technique can be used. This technique allows us to calculate how digit distributions diverge from the predictions of Benford's Law over time.

Continuous auditing using Benford's Law helps auditors analyze data in a continuous manner and assemble an audit sample for further investigation. If the dataset does not conform to the predictions of Benford's Law's, it does not necessarily mean that there is fraud in the respective dataset, only that the dataset requires further investigation. Therefore, the use of Benford's Law in continuous auditing reveals audit samples that should be further examined; it does not expose fraudulent records.

In this study, we analyze whether Benford's Law analyses can be used in continuous auditing methods for SMEs (Small to Medium-sized Enterprises). We developed a continuous auditing implementation of Benford's Law for a business hotel located in Ankara. Along with the hotel managers, we determined which account was most prone to manipulation. After specifying this account, which was the record of the hotel's receipts and invoices, we developed a script written in the R programming language to conduct a Benford's Law analysis on weekly basis. The hotel used an Structured Query Language (SQL) database, and we analyzed its data for 2020. To obtain a meaningful Benford's Law analysis result, the frequency of the analysis was crucial given that the quantity of records for SMEs is limited. We decided to conduct weekly analyses and then compare the results with monthly analyses to determine which was most appropriate. While comparing the differing frequencies of the test, another question for which we sought an answer was which dataset to analyze: the cumulative one or a non-cumulative one that included values only from the related time intervals. The cumulative data offered us relative discrepancies ratios, which allowed us to observe how digit distribution changed in time (Silva, Travassos &

Costa, 2017). With these two questions in mind, we analyzed the possible applications of continuous auditing combined with Benford's Law for SMEs in Turkey.

This thesis is organized as follows. Chapter 2 covers the literature on auditing, continuous auditing, and Benford's Law. Chapter 3 poses the research question and establishes the methodology used to conduct continuous auditing using Benford's Law for an SME in Turkey. Chapter 4 explains the results, and Chapter 5 summarizes the study, discusses the results, and suggests further implications.



CHAPTER 2

LITERATURE REVIEW

2.1 Auditing

Auditing is the process of reviewing an institution's financial records to see whether they follow regulations and policies. Also, during the audit, financial records are checked for accuracy.

The audit analyzes the accuracy of financial statements prepared by enterprises and their accordance with predetermined laws, procedures, and practices. The judgment is based on evidence. Auditors collect sufficient evidence to verify acceptable assurance and tests it. At the end of the audit period, they publish the results in a report (Utku & Kaya, 2020). There are basically three types of auditor, the most common of which are internal and external auditors. Internal auditors are employees of the company being audited, while external auditors work for an independent company which main business is auditing. Independent auditing companies are contracted to audit a client company for a specified period and a predefined purpose (Gray, 2008). There is a third type of auditing which is government auditing. Government audits are performed by government entities. The main purposes are to ensure that financial reports are being prepared accurately and there are no mistakes with respect to taxable amounts. If government auditors detect a mistake in the reports and the company does not accept the mistake, legal procedures begin to determine the outcome.

In the twenty-first century, auditors are needed more than ever because fraud rates have considerably increased. The latest Global Economic Crime Survey conducted in 2020 by PricewaterhouseCoopers (PwC) included 5000 participants from

99 territories, over 24 months. Fraudulent events were detected in 47% of companies and cost more than \$42 billion (PricewaterhouseCoopers, 2020). As fraud rates increase, we need to develop new methods to detect them. Before 1989, traditional auditing was the only option. Groomer and Murthy then proposed the alternative technique of continuous auditing (Groomer & Murthy, 1989).

2.2 Traditional auditing

Traditional auditing is conducted by external auditors. The auditors visit the client during the period of auditing. They gather the data from a client and analyze it according to predetermined rules and orders. In the meantime, they meet face to face with the client's representatives and have the opportunity to communicate with them if they need an explanation of the records.

Once the initial agreement between the auditing company and auditee is established, an auditor assesses risks and develops an audit plan. The audit plan defines the audit's scope and objectives. After that, the auditors gather and analyze evidence. Auditors develop an opinion about the reliability of internal controls and the information provided by the administration. At the end of the engagement, auditors submit a formal report expressing their judgment (Byrnes, Al-Awadhi, Gullvist, Brown-Liburd, Teeter, Warren, & Vasarhelyi, 2018).

Audit reports provide some level of assurance about the business environment, and they are written in a well-structured language. For people not familiar with the language of audit reports, they can be confusing. The two different types of audit reports are called unqualified and qualified reports. Those unfamiliar with auditing language might think that the qualified report is good and the unqualified one bad. However, the opposite is the case. After completing the auditing of the financial

statements, the auditor writes a “disclaimer,” “unqualified,” “adverse,” or “qualified” report to indicate his view considering the financial information presented. A disclaimer report is issued when there is a limitation that prevents the auditor from collecting the necessary evidence and the auditor is therefore unable to state a definitive opinion on the financial statements. An unqualified report is published when the auditor decides that the financial statements provide a real, fair summary of the company's situation and they comply with the predetermined financial reporting framework. An adverse report declares there are material problems with the financial statements. If auditors can share their view of the financial statements but the statement additional, specific, important financial information need to be released, a qualified report is published (Ibrahim, Ali, Ismail, & Bidin, 2020).

In traditional auditing institutions are audited periodically one, two, or four times a year. With technological advances in contemporary auditing, auditors are supported by computers, but ultimately human beings collect the data and have a role in some part of the process of analysis. Which is to say, traditional auditing is ultimately an analog system that necessitates human involvement. Technological deficiencies and time limitations typically force auditors to use sampling in testing financial records (Chan & Vasarhelyi, 2011). As such, traditional auditing cannot meet the needs of the contemporary business environment and is outdated. While external auditors are a third party, there are also internal auditors who analyze company records and assess risk internally.

2.3 Internal auditing

Internal auditing is an autonomous, objective assurance and counseling method. It adds value and progress to an organization’s operations and targets by bringing a precise

approach to assess and increase the effectiveness of hazard administration, control, and forms of administration. Internal auditing accomplishes this by teaching and making suggestions based on evaluations of information and business forms. With its commitment to judgment and responsibility, internal auditing gives confidence to administrative bodies and senior administrators as objective sources of autonomous advice. Organizations either employ experts for the task of internal auditing or they sign a service contract with an external supplier (IIA, 2004).

Internal auditing originally arose from the need for financial control function and was limited to this scope: measuring and evaluating the effectiveness of distinctive sorts of control, assessing the correctness of financial transactions, and checking for compliance with applicable laws and procedures. However, the scope of internal auditing widened in time (Sarens, & De Beelde, 2006). Today, it may include organizational administration, hazard administration, and administrative controls over operational efficiency; the reliability of reporting considering financial and administrative activities; and accordance with laws and regulations. Moreover, internal auditing is proactive. The scope of internal auditing covers proactive fraud audits to identify potentially fraudulent acts and control breakdowns (Alias, Nawawi & Salin, 2019).

The word auditor originates from Latin and means “listener.” The main duty of auditors is to listen carefully, evaluate the situation using their specialized knowledge and experience, and determine whether the statement is consistent with regulations and reality. Contemporary internal auditors are expected to have a wide range of knowledge and experience. The polished skills that expert auditors ought to possess are obtained from education, on-the-job training, and involvement in audits. Hence, lawmakers set the requirements that qualified individual auditors must meet to

be entitled to perform audits. To make their professional judgments, auditors must have knowledge and experience in distinctive disciplines. Expertise is not just a prerequisite for auditors to form judgments on a certain subject; it is the foundation upon which the perceived reliability of the audit is built. Managers and employees only accept the opinions of internal auditors if they trust that the auditor has sufficient knowledge and experience. Becoming an internal auditor is in today's business world is thus quite difficult (Paape, 2007).

Traditionally, internal auditing work is designed to assure reliable accounting records and to protect company assets. Nowadays, internal auditing is expected to include such fields as operational auditing, risk assessment, and information technology assurance. As part of the organization's administrative control structure, the significance of internal auditing has expanded; however, the requests made of internal auditors have also evolved. Their modern role requires distinctive competencies, and organizations face the choice of whether to create these broad competencies internally or to outsource internal auditing to external service suppliers (Spekle, Van Elten, & Kruis, 2007). Another option is to hire an experienced professional.

Execution of organizational activities is not part of the job definition of internal auditors. They counsel administrators and executive boards to better deliver their contractual obligations. Because internal auditors have a wide scope of responsibility, varied educational and business-related backgrounds are sought among auditors.

Changes to recording systems and technological developments make it possible to minimize human interaction in the auditing process. Also, technological developments permit auditing to be realized more frequently than one, two, or four times in a year. A new trend in auditing, called continuous auditing, has gained

importance as it targets minimizing human involvement in the auditing process and maximizing the use of computer programs.

2.4 Continuous auditing

Changes in business dynamics are inevitable. Developments in business technology are becoming more complex every day, and businesses are compelled to adopt these new technologies to protect or extend their positions in the market. With the spread of technology in the business environment, the economic pace has increased and new systems are continually being developed to make the departments or units of businesses faster and more effective. New recording systems are being developed for accounting departments that companies use to adapt to the new business environment. As recording systems change, the stasis of auditing methods is unsustainable. Information technologies are becoming more complex and traditional auditing methods are losing their dependability. Recording in complex file structures has made traditional auditing more time-consuming if not useless. Thus, auditors have sought new method, of which continuous auditing is the best for this new business environment (Warren & Smith, 2006). Because all financial records in databases, it is possible to benefit from continuous auditing systems.

Continuous auditing is a new method of conducting auditing. It is a real-time system that makes it possible to collect and pursue integrated data and provide reliable financial information (Moon & Krahel, 2020). Continuous auditing systems can be used to monitor, analyze, and audit financial records. Because it is a paperless real-time system, it is possible to test records more frequently if not continuously. Continuous auditing is continuously and minimizes human involvement in the process. Algorithms and analytic tools are used in continuous auditing, and while external

auditors still exist in this system, their role is to assent to the audit reports. Due to the lack of time limitations and the continuous structure of the process, complete data rather than samples are being tested by the system (Chan & Vasarhelyi, 2011).

In traditional auditing, accounting records are audited periodically one, two, or four times a year. Material errors, fraud, and negligence can remain undetected for months before being noticed, which negatively affects companies, investors, and the market. Continuous auditing eliminates this risk because it takes place on a more frequent or continuous basis. This continuous monitoring and testing of records allows market players to detect and investigate problems as they are taking place rather than reacting to them long after they occurred. To sum up, while traditional auditing is a reactive method, continuous auditing is proactive. As computer-based accounting systems have become more complex and detailed for each unit of a business, proactive auditing has become more meaningful. Continuous auditing reduces the negative impact on the market of errors, fraud, and negligence that are contemporaneously becoming more frequent (Chan & Vasarhelyi, 2011).

2.4.1 A brief history of continuous auditing

Automated accounting records started to be used in the early 1960s. In this long journey, the first step was the creation and implementation of embedded audit modules (EAMs). The setup and maintenance of such embedded audit modules were complex. Unfortunately, at the time the relevance of these embedded audit modules for the market could not be proved. Auditors' approaches to the new computer-based systems started to change by the late 1970s. By the 1980s, in the audit business early adopters of computer-assisted audit tools and techniques (CAATTs) started to emerge in the auditing business. At the same time, the concept of continuous monitoring in auditing

was first introduced, though largely in the academic context. Its main purpose was to allow auditors to benefit from continuous, automated data analysis systems to identify risky areas and prepare audit plans. But auditors were not ready for this approach. They did not have the tools, technical equipment, and know-how to cope with the problems of access to digital data. Most significantly, auditors did not receive the support of auditing companies that lacked the organizational will to acknowledge and commit to a significantly different approach and methodology (Coderre, & Police, 2005).

By the 1990s, the popular acceptance and movement toward automated data analytics solutions began, and data analytics solutions were considered an important tool for the analysis of the effectiveness of internal controls. Data analytics solutions were used to test transactions for the symptoms of a lack of control. Moreover, these systems detected records that were inconsistent with control standards. The novelty was that data analysis also assisted the analysis of controls not directly related to transactional records. For instance, enterprise resource planning (ERP) access and authorization tables were tested for errors to pursue proper division of labor. But even as the foundation of data analytics solutions was laid, traditional audit processes continued to rely on sampling rather than the testing of the whole of the records. And testing continued to occur sometime after the business activity had taken place. Issues of risk and control still had significant opportunities to escalate and negatively affect business performance (Coderre, & Police, 2005).

2.4.2 Continuous assurance

Assurance can be defined as the comment of a third party about the situation of a case, operation, financial record, or management process. In the field of assurance, there are three relevant parties: the first generates and shares the information, the second makes

decisions based on the information shared by the first party, and the last is the objective one. Audit assurance is the declaration of that proper checking of the information and its compliance with regulations and laws. Testing management activities, confirming that checks are working, advising improvements, and securing risk management are the duties of the auditors. A higher level of assurance is ensure by better auditing (Coderr & Police, 2005). Certifying the integrity of the shared information is the main purpose of auditing. Continuous auditing provide continuous assurance, and continuous assurance offers continuous security for decision-makers rather than periodic reassurance.

2.4.3 Continuous control assessments

Auditors reassure management that control mechanisms are working adequately and report problems and mistakes. This is important because confirmation is the basis of auditing. To ensure control assessment, individual records are checked according to rules of control. The conclusions are scrutinized to see if any exceptions are occurring. If there is are exceptions, a control model is developed. Control rules are crucial because they pinpoint problems in the control model. Perfected control rules can signal an early warning if the control model is not functioning as promised (Coderr & Police, 2005). Continuous assurance only make senses if continuous control assessments are done properly.

2.4.4 A comparison of traditional auditing and continuous auditing

A comparison of traditional and continuous auditing brings the importance of continuous auditing to light. As mentioned above, traditional auditing is a periodic method whereby institutions are monitored one, two, or four times in a year. In

continuous auditing, due to its real-time structure, auditing is unremitting. While with traditional auditing, errors or fraud are only detected during the auditing period, which means it possible that fraud will be identified only three months, six months, or maybe even a year after the fact. In continuous auditing, errors and fraud are detected simultaneously with their occurrence. In the new business environment, it is crucial for companies to be able to detect and solve such problems immediately. Traditional auditing is thus outdated for this new business environment, continuous auditing matches the demand perfectly.

Traditional auditing is supported by computers, but the system is still ultimately manual and open to human error. On the other hand, continuous auditing is a completely automated, paperless, real-time method. External auditors are present in each method, but their roles in the process differ. In traditional auditing, auditors sample financial records, analyze them, and report on them. Auditors in continuous auditing hold the position of certifying the audit report; the records themselves are analyzed by algorithms. Human intervention in the processes of recording and auditing increases the possibility of error and fraud. This intervention in the audit process is minimized in continuous auditing, reducing the possibility of human error or manipulation. Continuous auditing is thus a better method in terms of security and reliability.

In traditional auditing, auditors apply sampling at the analysis stage. Because of time limitations and the vast amount of data, sampling is the best option given that, as mentioned, traditional auditing is manual. Even so, auditors scientifically calculate their sample sizes and determine which records will be in the sample. Which is to say, auditors report only on the records that they have selected for testing; unselected records remain unaudited. It is also possible for auditor to selectively ignore errors or

fraud and select other records for their report instead of incongruous ones. To overcome this issue, continuous auditing is the best alternative. In continuous auditing, there is no sampling. Algorithms test the whole of the data and provide the report automatically. If there are any errors or fraud in the records, it will appear in the audit report without question.

2.4.5 The importance of the model

Continuous auditing is a method of auditing. There are several methods by which to realize continuous auditing. With technological improvements, new models are being developed to increase the effectiveness and efficiency of audits. The selection of the algorithms and software to be used in the models is crucial. It is possible to develop a perfect model with the proper choice of tools. Technological developments bring new tools into existence every day. In this thesis, we propose a model that involves Benford's Law and an R script. This model detects error and fraud records on a more frequent basis.

To realize the audit, we needed to create a sample because it was not possible to check all the records of the company. There are several ways to compile an audit sample. In our case, we benefited from Benford's Law, a technique with a long history. It is a mathematical law that identifies suspicious records by considering the relative frequency of the first digit of numerals in the records. Because Benford's Law has been repeatedly tested and has been used for a long time, we decided to utilize it to create the audit samples for our data sets.

2.5 Benford's Law

Benford's Law is an assessment of the first digits of numbers in real-world data collections. The law predicts the natural distribution of digits in numbers. The popular guess of the natural distribution of digits in numbers is that they would be equal; that is, there is an equal chance of the digits from 1 to 9 to appear as the first digit in numbers. However, the reality is different. Usually, 1 emerges more commonly than 2, and 2 more often than 3, and so on. This is a simplistic account of Benford's Law. More specifically, by utilizing base-10 logarithms, the law forecasts the frequency of the first digits of numbers. The frequencies of each digit reduce as the digit increases from 1 to 9. In cases of datasets without human manipulation, Benford's Law applies. When data from various sources are combined, the law is even more likely to stand. While Benford's Law does not apply to every type of dataset, it should apply if the datasets meet certain, pre-defined conditions. Furthermore, the areas of implementation of the law are wide-ranging.

2.5.1 The history and mathematics of Benford's Law

Benford's Law, also called the first-digit law, has long been considered an amazing law of nature. It has a wide range of applications from fraud detection to computer disk space allocation. The story of Benford's Law started in 1881 when an American astronomer Simon Newcomb noticed that the early pages of logarithm books were always dirtier than those toward the back of the books. Before pocket calculators became available in the 1970s, scientists and engineers used logarithms to multiply big numbers. To multiply two numbers together, they would first check the logarithms in the book and then add the logarithmic values together to find the anti-logarithm of the sum. Scientists and engineers made calculations with numbers beginning with 1

and 2 far more often than with the digits 8 and 9, and Newcomb suggested that the probability of the first or leading digit d was

$$P(\text{leading digit} = d) = \log_{10} \left(\frac{d+1}{d} \right), \quad d = 1, 2, \dots, 9$$

In 1938, Frank Benford, a physicist working for General Electric, assembled over 20 thousand numbers from several, unrelated sources like articles, addresses, weights, and populations. The result of Benford's analysis was to confirm Newcomb's logarithmic model. Benford gave his own name to the law (Fewster, 2009).

In 1938, Benford published the article entitled "The Law of Anomalous Numbers" in the journal of the American Philosophical Society. He explained his study of the 20 thousand unrelated numbers and his conclusion. He grouped the numbers according to their first digit (Benford, 1938).

PERCENTAGE OF TIMES THE NATURAL NUMBERS 1 TO 9 ARE USED AS FIRST DIGITS IN NUMBERS, AS DETERMINED BY 20,229 OBSERVATIONS

Group	Title	First Digit									Count
		1	2	3	4	5	6	7	8	9	
A	Rivers, Area	31.0	16.4	10.7	11.3	7.2	8.6	5.5	4.2	5.1	335
B	Population	33.9	20.4	14.2	8.1	7.2	6.2	4.1	3.7	2.2	3259
C	Constants	41.3	14.4	4.8	8.6	10.6	5.8	1.0	2.9	10.6	104
D	Newspapers	30.0	18.0	12.0	10.0	8.0	6.0	6.0	5.0	5.0	100
E	Spec. Heat	24.0	18.4	16.2	14.6	10.6	4.1	3.2	4.8	4.1	1389
F	Pressure	29.6	18.3	12.8	9.8	8.3	6.4	5.7	4.4	4.7	703
G	H.P. Lost	30.0	18.4	11.9	10.8	8.1	7.0	5.1	5.1	3.6	690
H	Mol. Wgt.	26.7	25.2	15.4	10.8	6.7	5.1	4.1	2.8	3.2	1800
I	Drainage	27.1	23.9	13.8	12.6	8.2	5.0	5.0	2.5	1.9	159
J	Atomic Wgt.	47.2	18.7	5.5	4.4	6.6	4.4	3.3	4.4	5.5	91
K	$n^{-1}, \sqrt{n}, \dots$	25.7	20.3	9.7	6.8	6.6	6.8	7.2	8.0	8.9	5000
L	Design	26.8	14.8	14.3	7.5	8.3	8.4	7.0	7.3	5.6	560
M	<i>Digest</i>	33.4	18.5	12.4	7.5	7.1	6.5	5.5	4.9	4.2	308
N	Cost Data	32.4	18.8	10.1	10.1	9.8	5.5	4.7	5.5	3.1	741
O	X-Ray Volts	27.9	17.5	14.4	9.0	8.1	7.4	5.1	5.8	4.8	707
P	Am. League	32.7	17.6	12.6	9.8	7.4	6.4	4.9	5.6	3.0	1458
Q	Black Body	31.0	17.3	14.1	8.7	6.6	7.0	5.2	4.7	5.4	1165
R	Addresses	28.9	19.2	12.6	8.8	8.5	6.4	5.6	5.0	5.0	342
S	$n!, n^2 \dots n!$	25.3	16.0	12.0	10.0	8.5	8.8	6.8	7.1	5.5	900
T	Death Rate	27.0	18.6	15.7	9.4	6.7	6.5	7.2	4.8	4.1	418
Average		30.6	18.5	12.4	9.4	8.0	6.4	5.1	4.9	4.7	1011
Probable Error		± 0.8	± 0.4	± 0.4	± 0.3	± 0.2	± 0.2	± 0.2	± 0.2	± 0.3	—

Figure 1. Benford's observations (Benford,1938)

The data sources and the distribution of numbers derived from these sources with respect to the whole can be observed in Figure 1. These are the rates of the frequencies of given first digits. Even though the groups individually did not perfectly follow Benford's Law, collectively they closely corresponded to it.

The logarithmic function $F_a = \log\left(\frac{a+1}{a}\right)$ closely provides the frequency of the first digit. F_a is the frequency and a is the first digit.

Benford further developed the logic and introduced formulations for the frequencies of digits in the second and q th places (Benford, 1938).

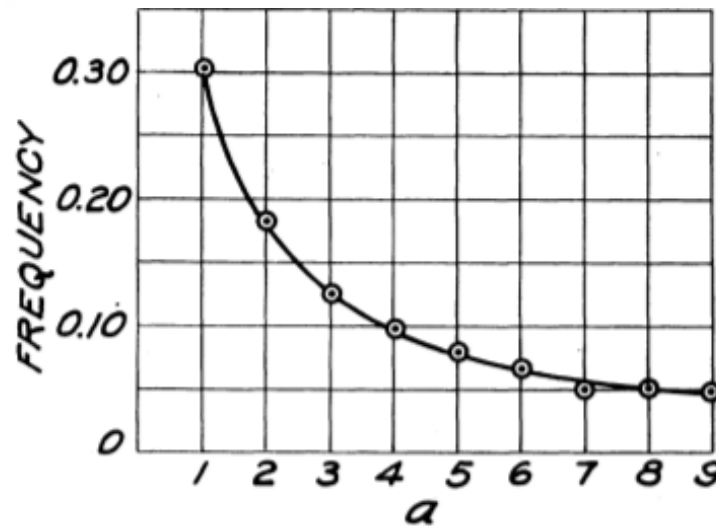


Figure 2. Frequency of digits in the first place (Benford,1938).

As seen from in Figure 2, 1 and 2 are the most common digits in the first place. As the place within the number increases, the frequency of these digits decreases.

In the function above, a indicated the first digit. In the formula for calculating the frequency of digits in the second place, the first digit a remains part of the equation while b stands for the second digit. That is to say, the number in the first digit affects the frequency of the second digit. Also, zero is an additional option for the second digit, bringing the number of options for the second digit up to ten rather than nine for the first digit (Benford, 1938).

$$F_b = \log\left(\frac{ab+1}{ab}\right) / \log\left(\frac{a+1}{a}\right)$$

In this logarithmic function, F_b stands is the frequency and b is the digit in the second place. The function below can be used to calculate the frequency of q th digit (Benford, 1938).

$$F_b = \frac{\log \frac{abc...p(q+1)}{abc...pq}}{\log \frac{abc...o(q+1)}{abc...p}}$$

2.5.2 Benford's Law requirements

Benford's Law has a wide range of applications, but it does not apply to every case. There are certain requirements for it to be applicable.

First, the dataset needs to consist of values of a similar phenomenon. The dataset cannot contain entries from two different phenomena. Second, there should be no preset minimum or maximum value; artificial beginning or ending values make Benford's Law inapplicable. Third, the dataset must not contain assigned numbers like identification numbers or phone numbers. Given these requirements, Benford's Law is applicable to auditing and accounting (Lu, Boritz & Covvey, 2006).

2.5.3 Benford's Law application to auditing and accounting

Auditors benefit from different tools while performing analytical procedures. Benford's Law is one. It can be used to check entire accounts or records to see whether they fall into the expected distribution. Although Varian suggested that Benford's Law could be used in the social sciences to test data quality, it was in 1972 that the researcher Mark Nigrini first applied Benford's Law to accounting to detect fraud (Durtschi, Hillison, & Pacini, 2004).

Nigrini is the father of the use of Benford's Law in accounting. He pioneered its use to pinpoint tax evasion and various forms of financial fraud. When employees

need to create fraudulent records for their benefit, they tend to create numbers with equal distribution of digits to make it look natural. These numbers, of course, do not correspond to Benford's Law and are easily detected. Numbers created taking Benford's Law into consideration are detected due to the double-entry accounting system. Because they are created to balance books and correct the misappropriation of funds, the flip side of the record entry cannot simultaneously be created considering Benford's Law. If the total is divided and recorded as many small entries, then it will not correspond to Benford's Law and will be easily detected. If not divided and recorded as is, then the large amount of the entry will attract attention. Because Benford's Law does not concern only the first digit and its distribution among the sample, the distribution of the q th digit allows the fraud to be detected. So whether divided into many records or recorded as a single entry, this human-made number will be detected by Benford's Law. Benford's Law is a signature of naturally created numbers (Kumar & Bhattacharya, 2007).

In today's world, Benford's Law is a popular tool in auditing. As mentioned, the tool analyzes numerical patterns of digit occurrence to detect fraud, irregularities, and biases. Auditors analyze the distribution of digits in the dataset and compare it with the distribution rates predicted by Benford's Law. If there is a significant difference between the two, this is a flag that further analysis of the respective dataset is necessary.

2.5.4 Best practices in the application of Benford's Law

In the process of applying Benford's Law to the detection fraud, the main problem is that many datasets do not meet the prerequisites for Benford's Law. There are general rules to distinguish whether or not a dataset is appropriate for Benford's Law testing;

however, there is no absolute test to separate the two. For example, consider a scenario in which the leading digit distribution of a financial dataset sharply differs from the Benford's Law distribution while those of similar datasets correspond to Benford's Law. In this scenario, it is possible to suspect fraud or manipulation of the data from the perspective of Benford's Law (Pimbley, 2014).

The result of a Benford's Law test does not indicate which values are true or produce any distinguishing information regarding the distribution of the leading digits. Moreover, it is scientifically impossible to confirm that a given natural dataset must match the Benford distribution. Therefore, the main goal of a Benford test is to mark particular datasets for further analysis rather than to definitively assert irregularities. In many cases, Benford's Law is useful, but financial risk managers and investigators must constantly employ additional methods for the analysis of data reliability (Pimbley, 2014).

2.5.5 Continuous auditing with Benford's Law

In 2020, Singh and Peter implemented two tests for two organizations: a government department and a global manufacturing company. They supplemented a continuous Enterprise Resource Planning (ERP) system with a Benford's Law test. According to their study, this method enabled them to analyze the population of records for a predetermined time period. The most important contribution of the study was that they demonstrated how Benford's Law could be used in continuous monitoring systems. It provided assurance to the company and related personnel when needed; they did not need to wait for the audit period for this reassurance (Singh & Peter, 2020).

In the continuous auditing method, datasets are analyzed in a time series. In traditional auditing, Benford's Law is used in the context of the Benford analysis

technique, but this technique is not suitable for time series analysis. Benford analysis is an observation of a dataset at a specific point in time. However, for continuous auditing, a technique based on Benford's Law is needed that will enable time-series analysis. Relative discrepancies is just such a technique.

2.6 Relative discrepancies

In 2017, Silva et al. analyzed 210,899 contracts issued by sixty management units in two states in northeast Brazil in 2010. In their Benford's Law test, Z-score and chi-square values were used. However, because the samples are related to each other, these values are useless for continuous auditing. Silva et al. suggested a time-series analysis technique using Benford's Law and continuous auditing. They calculated and analyzed the distribution of relative discrepancy values within a specified time series. They defined relative discrepancies as the ratios of the differences between observed digits frequencies and frequencies predicted by Benford's Law over the respective expected frequencies. They concluded that the accuracy of sampling procedures in continuous auditing can be improved by a time series analysis of Benford's Law (Silva et al., 2017).

Time series analysis cannot be performed using Z-score and chi-square techniques. However, they needed to conduct a Benford's Law analysis in time, so they calculated the relative discrepancies, which is the ratio of how the digit distribution in the dataset diverged from Benford's expectations. They calculated this ratio frequently to determine how the digit distribution in the dataset deviated from expectations in time.

$$Dri(t) = \frac{Poi(t) - Pei}{Pei}$$

In this formula;

- i stands for first digit numbers from 1 to 9,
- t stands for time,
- Dr stands for the discrepancies ratio,
- Po stands for the observed ratio, and
- Pe stands for the expected ratio (Silva et al., 2017).

This technique enables auditors to analyze related data within a time series using Benford's technique. The analysis of digit distribution in a time series and the comparison of multiple digit distributions made this technique more appropriate for time series data analyses (Silva et al., 2017).

Even though auditing companies using paperless, real-time systems need continuous auditing, audit samples remain necessary. Benford's Law is a mathematical law long used to create audit samples. Because of the nature of continuous auditing, a technique that allows time-series analyses is necessary. Relative discrepancies is such a technique based on Benford's Law that permits time series analysis.

CHAPTER 3

RESEARCH QUESTION AND METHODOLOGY

3.1 The research problem

The problem is to analyze the proper use of Benford's Law within the technique of continuous auditing both to determine an audit sample and to warn of possible cases of fraud in SMEs in Turkey.

3.2 The purpose of the study

The aim is to investigate whether Benford's Law is an appropriate technique for fraud detection and to create audit samples in the context of continuous auditing of SMEs in Turkey. More specifically, the study analyzes the appropriateness of more frequent or continuous use of Benford's Law to detect possible fraud and build audit samples for further investigation.

3.3 The research questions

In this research, we tried to determine the proper frequency with which to execute Benford's Law analysis for Turkish SMEs as well as which dataset needs to be analyzed, the cumulative one or the one that includes only values from specific time intervals.

3.4 Methodology

In this thesis, we analyzed the effectiveness of using Benford's Law in continuous auditing. We implemented the analysis for a hotel in Ankara founded in 2013. We developed an R script to conduct the Benford's Law analysis and report the results to

the respective managers. Using the results, we analyzed how effective was the use of the Benford's Law technique for continuous auditing.

To obtain a meaningful Benford's Law analysis result, the frequency of the test is important. Because the volume of records for SMEs is limited, we decided to conduct analyses on weekly basis. After obtaining the results, we compared the results from the weekly analyses to monthly analyses to determine which frequency was more appropriate. However, this was not the only question that needed an answer. For the second – of whether to analyze the cumulative dataset or one that only includes values from the related time intervals –we compared the results from both.

Our R code connects to the SQL database of the hotel and after conducting analyses writes the results to Google Docs files for the respective managers to review each week. The code is triggered by PowerShell, So it is continuous and conducts analyses regularly.

For the Benford's Law analyses we used the `benford.analysis` package created by Carlos Cinelli and published in 2018. This open-source package was preferred because it has been repeatedly tested. Among those in the package, we used three main functions, the `Benford()` function, which basically realizes the Benford's Law test; the `Plot()` function, which creates tables of the results of the Benford's Law test; and the `getSuspects()` function, which returns the list of outlying records that most deviate from the predictions of Benford's Law (C.Cinelli, 2018).

3.5 Data scope

In this study, we analyzed the use of the Benford's Law technique in the context of continuous auditing in an SME in Turkey. For this purpose, we applied our model to a business hotel in Ankara as the subject of the analysis. In discussions with hotel

managers, we tried to determine the most fraudulent account, which was determined to be the record of the hotel's receipts and invoices. This account was suitable for our analysis because of the following:

- All the numbers were recorded in the same unit of measurement.
- There was no predetermined maximum or minimum number for the records in this account.
- The numbers were not assigned or determined according to predetermined rules (Singh, & Peter, 2020).

Records related to specified accounts were copied from the hotel's comprehensive SQL database to an SQL table built for the purposes of this research. The dataset included only records since the beginning of 2020 as this is when the hotel began using an SQL database. Thus the cumulative data was limited in scope to 2020. Our R script conducted its analyses and reporting every Sunday starting on 29 November 2020. However, this study only considers the analyses of cumulative and non-cumulative datasets from 29 November 2020, 6 December 2020, and 3 January 2021.

We chose these three dates to investigate the best frequency for this analysis. Considering the low number of daily new records of the SME, it was meaningless to implement a daily analysis, so we decided to compare the results of analyses conducted on a weekly and monthly basis. To obtain weekly and monthly datasets, we set these three dates for consideration. However, we also needed to ascertain the best dataset type: cumulative or non-cumulative. The cumulative datasets consisted of all of the records from the beginning of 2020 to the date of a given analysis. The non-cumulative datasets included only entries recorded between the dates of two subsequent analyses. As mentioned above, we have several datasets for the three different dates. The 6 December 2020 cumulative dataset included records from 1 January 2020 to

6 December 2021. On the other hand, the 06 December 2020 non-cumulative dataset included only entries recorded between 29.11.2020 and 06.12.2020.

Table 1. Number of Records

Date	Number of Cumulative Records	Number of Non-Cumulative Records
29/11/2020	1040	-
06/12/2020	1062	22
03/01/2021	1148	108

Table 1 compares the number of records in the respective datasets. The first column identifies the dataset, the second provides the cumulative number of records since 01/01/2020, and the third column indicates the non-cumulative number of records. In other words, for 06/12/2020 and 03/01/2021 the last column indicates the number of records recorded between 29/11/2020 and the respective date. These are the sizes of datasets used in our analysis.

3.6 Data analysis

In this study, we tried to determine the proper frequency with which to execute Benford's Law analysis for SMEs in Turkey as well as which dataset needs to be analyzed, cumulative or non-cumulative. For this purpose, we analyzed data on different dates. We first applied the Benford's Law technique and then, according to the results, we pulled out suspicious records. Lastly, we compared the results to determine the most effective application of continuous auditing with Benford's Law to SMEs in Turkey.

In the first step of the analysis, we used Benford analysis to determine whether the datasets matched with expectations. We implemented this technique on five datasets gathered on three different dates. This analysis provided the distribution of first digits in the datasets.

In the second step, we calculated the relative discrepancy ratios for cumulative datasets. In calculating this ratio, we benefited from Silva et al. (2017) study. Because Z-score and chi-square techniques cannot be used to analyze data over time, Silva et al. calculated the differences between the frequencies of digits observed and their expected distribution according to Benford's Law $[(poi - pei), i = 1, \dots, 9]$ over the expected distributions ratios.

$$Dri(t) = \frac{Poi(t) - Pei}{Pei}$$

In this formula,

- i is the first digit in the number from 1 to 9,
- t stands for time,
- Dr is the discrepancies ratio,
- Po is the observed ratio, and
- Pe is the expected ratio (Silva et al., 2017).

With this formula, it is possible to observe how digit distribution changed in time. This technique enables auditors to analyze related data in a time series. Changes in digit distribution can be analyzed in comparison with other digit changes. The opportunity to analyze digit distribution in a time series and the possibility to compare distinct digit distributions make this technique more robust for cumulative data analyses.

To determine the best frequency for obtaining meaningful results from Benford's Law analysis, we compared cumulative and non-cumulative dataset results for these three dates. In the process, we compared to what degree Benford analysis results diverged from the predictions and which place in the number deviated most.

To find out which dataset needed to be analyzed, we compared the results from cumulative and non-cumulative dataset for these three dates; that is, we compared how much the results of Benford analyses diverged from predictions. Again, the place of

the digit that diverged most from the predictions was another point of comparison. The most crucial point of the analysis was to compare the results of relative discrepancies analyses with those of non-cumulative Benford's Law tests. In this way, we ascertained whether or not time-series analyses were more valuable.



CHAPTER 4

RESULTS

4.1 Benford analysis

We implemented Benford analysis on five different datasets: three cumulative and two non-cumulative datasets compiled on three different dates. These three dates were spaced on week and one month apart. This part analyzes the results of each of these Benford analyses individually. Only according to the results can we compile an audit sample from the cumulative monthly-based dataset.

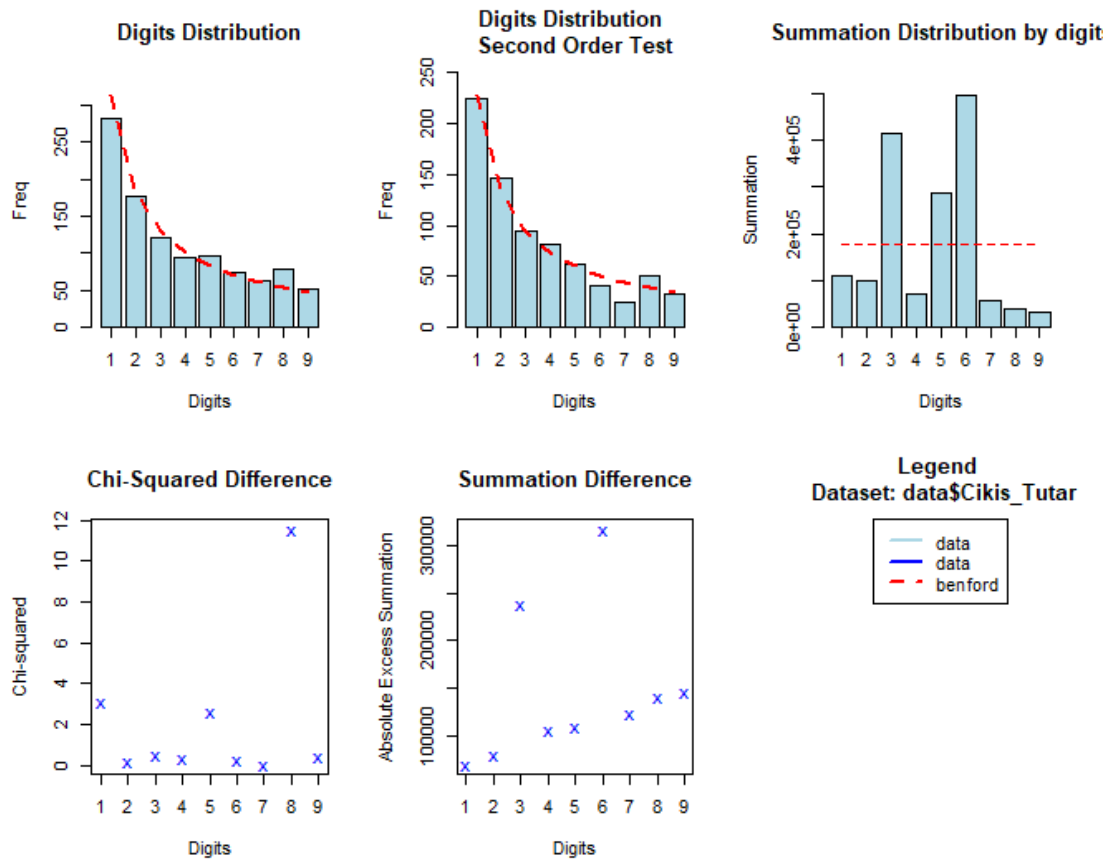


Figure 3. Benford analysis dated 29.11.2020

Figure 3 shows the results of the Benford analysis for 29.11.2020 data which included cumulative records from the beginning of 2020 to 29.11.2020. The Chi-Squared Difference graph clearly indicates that records starting with the digit 8 occur

significantly more than would be expected according to Benford's Law. Records starting with 1 follow. Indeed, the Digit Distribution graph suggests that records starting with 1 are less than Benford's Law expectations. Finally, records beginning with 5 are also more than Benford's Law predictions. So, we have fewer 1s and more 5s and 8s than Benford's Law would predict. But overall, the distribution is fair. These graphs are crucial for our analysis because we use them to compare with other dataset results in order to determine the best frequency and best type of dataset.

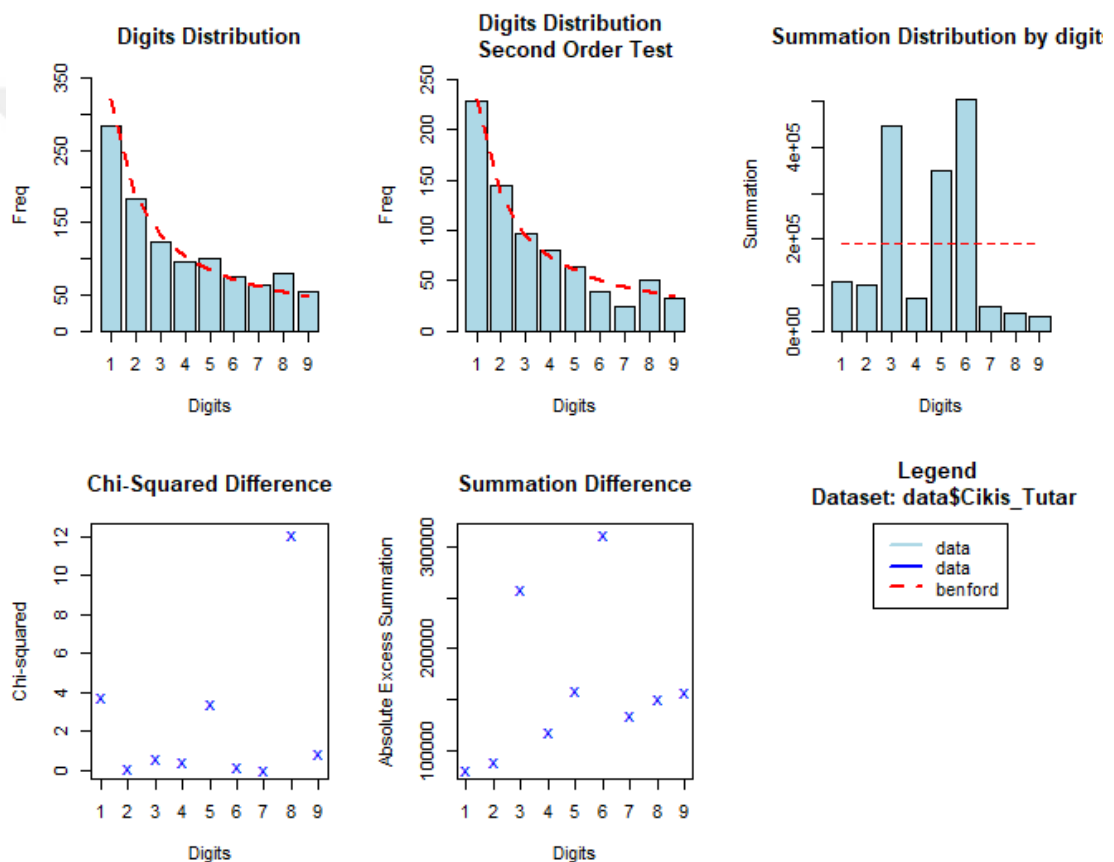


Figure 4. Benford analysis dated 06.12.2020 cumulative

Figure 4 is the results of Benford analysis for cumulative data starting at the beginning of 2020 up until 06.12.2020. The results are almost the same as for the 29.11.2020 dataset. Because our records are from an SME, the volume of weekly records is limited. The only difference between Figures 3 and 4 is the weekly records between 29.11.2020 and 06.12.2020. This comparison is a weekly cumulative test because both

datasets are cumulative and there is only one week's difference between the two dates. This result suggests that weekly cumulative analysis does not allow one to see the effects of new records. That noted, we continued with the Benford analysis of the non-cumulative dataset for this week.

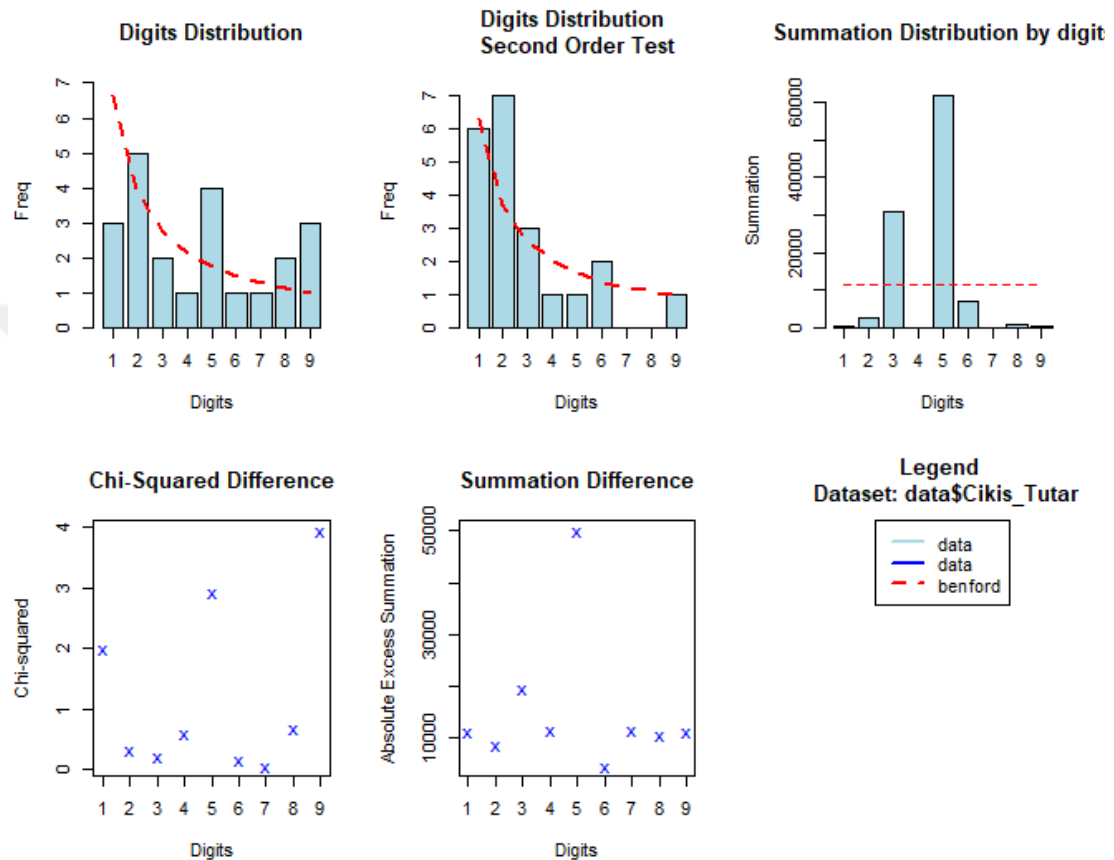


Figure 5. Benford analysis dated 06.12.2020 non-cumulative

Figure 5 covers the non-cumulative dataset of the week immediately prior to 06.12.2020. It includes the records of only the one week between 29.11.2020 and 06.12.2020. There were only 22 records in this week, so the size of the dataset was not suitable for Benford analysis. As seen from the result, the dataset does not harmonize with Benford's Law expectations. Clearly, this technique does not provide any meaningful information to our SME. Moreover, we cannot determine any meaningful sample among the new records for further auditing. Maybe we need to analyze on a monthly rather than weekly basis.

These two analyses show that Benford's Law is not useful for cumulative weekly datasets. Indeed, there was no noticeable difference in the results. Benford's Law cannot be applied to non-cumulative weekly datasets, either. The small size of the dataset is not suitable for Benford analysis.

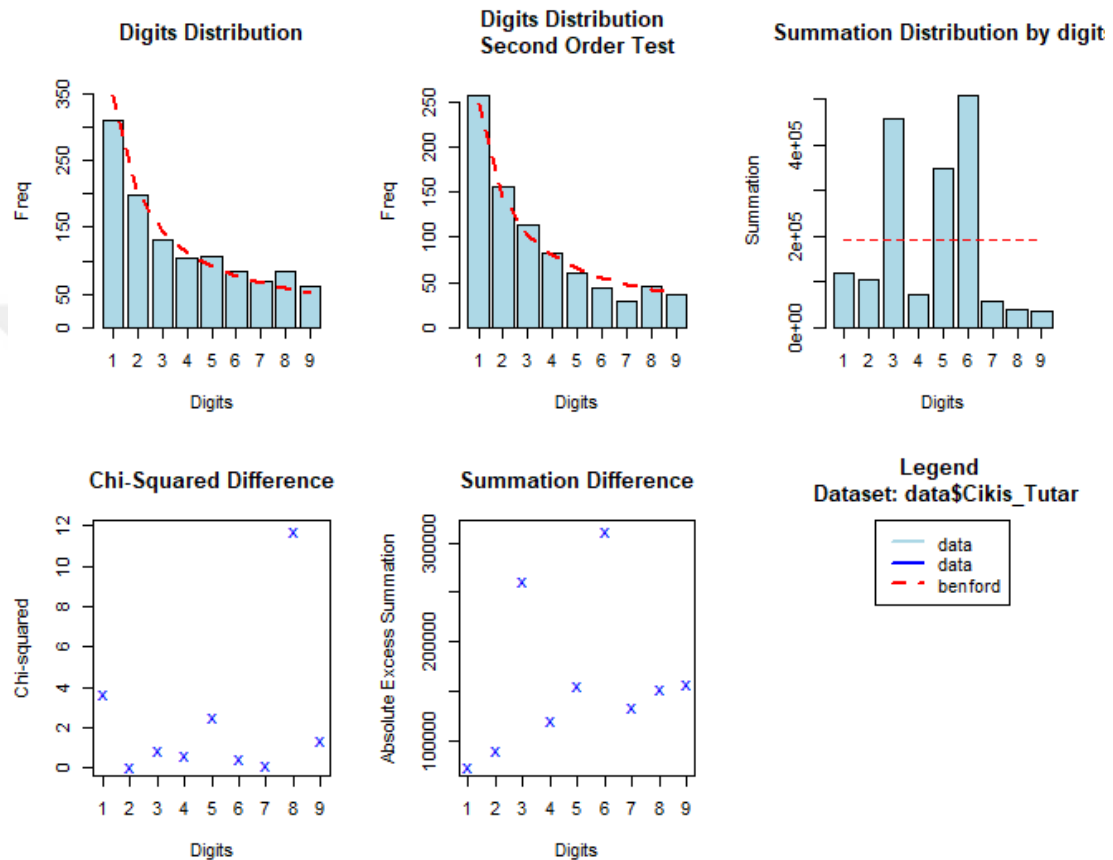


Figure 6. Benford analysis dated 01.01.2021 cumulative

Figure 6 illustrates the Benford analysis results of a cumulative dataset for the whole of 2020. Figure 6 will be compared to Figure 3. There is a one-month difference between the two, and both datasets are cumulative. In contrast with the results of the 29.11.2020 analysis, records starting with the digit 5 conform more closely to Benford's Law, while records starting with the digit 9 deviated from expectations. Changes in the results are significant and observable. Therefore, an audit sample for this period could be created from records starting with 9, which is to say that the

monthly cumulative test is sufficient to compile an audit sample. We then checked whether analysis of the non-cumulative dataset for the same period would yield the same result.

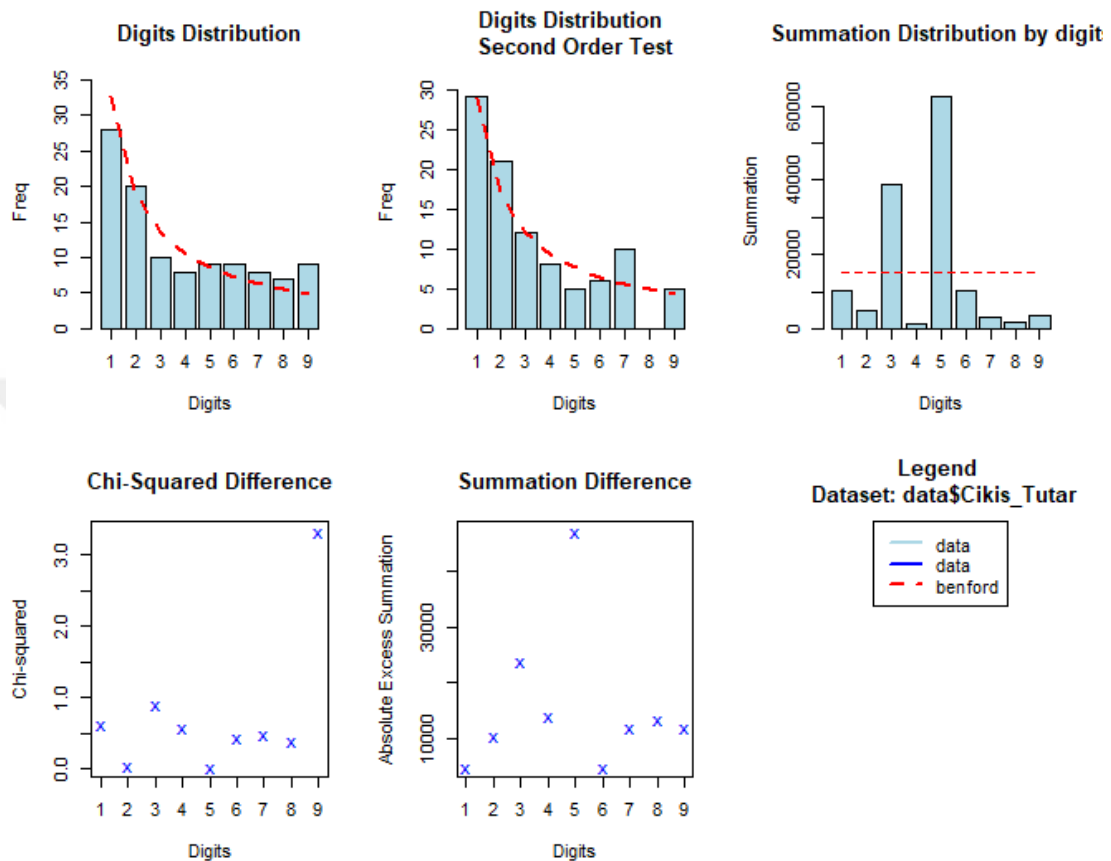


Figure 7. Benford analysis dated 01.01.2021 non-cumulative

Figure 7 shows the Benford analysis results for a dataset that includes only data on the month from 29.11.2020 to 01.01.2021 – that is, a non-cumulative monthly dataset. For this specific period there were 108 records, which is still an insufficiently large dataset for implementing Benford analysis. While the results may conform to Benford’s Law, no unnatural phenomenon can be blamed if it does not. In our case, though some numbers corresponded with the predicted distribution, an audit sample cannot be drawn from the analysis of this monthly non-cumulative dataset.

In sum, we could derive audit samples using Benford analyses of weekly datasets. Also, non-cumulative monthly datasets did not reveal any change over time.

The only scenario from which an audit sample could be derived was the cumulative monthly dataset. However, Benford analysis by itself does not allow for time-series analysis. For analyses over time, we benefited from the technique of Relative Discrepancies based on Benford's Law.

4.2 Relative discrepancies

With the Relative Discrepancies technique, it is possible to observe how digit distributions change in a time series. The analysis of digit distribution over time and the comparison of separate digit distributions make this technique more robust for cumulative data analysis. We analyzed the relative discrepancies in the cumulative dataset on a weekly basis on three different dates. This technique is also more efficient because companies may create new records for previous dates, and a cumulative time series analysis accounts for this kind of record.

For this technique, we calculated the distribution of each number in the time series and their relative discrepancies. The distribution and discrepancies tables for these three dates are in the appendix section (see Appendix A). With this type of analysis, we determined audit samples for both related time periods. We will explain the results one by one.

Figure B1 (Appendix B) shows the relative discrepancies for the dataset from the beginning of 2020 to 29.11.2020. From these graphs, we can analyze how digit distributions diverged from Benford's Law in a time series. Zero would indicate a perfect match with Benford's Law. Because the relative discrepancies technique uses cumulative data, it is possible to see how new records affect digit distribution in each number. At the beginning of each graph, almost every number deviated sharply from Benford's Law, but in time they start to approach zero. When we analyze, Except for

records starting with 8 and 5, all other digits in Figure B1 (Appendix B) have relative discrepancies less than 0.1. This ratio is relatively insignificant. But records beginning with the digits 8 and 5 need further investigation. A subset for auditing can be proposed consisting of records starting with 8 and 5. This analysis points to an audit sample for the full year up until 29.11.2020. Let us continue with the next dataset, which includes one additional week, to ascertain an audit subset for that specific, one-week period.

Figure B2 (Appendix B) indicates cumulative data from the beginning of 2020 up until 06.12.2020. We analyze how the previous week's records affected digit distribution and whether an audit sample could be proposed based on that information. Records starting with 1, 3, 5, and 9 significantly deviated from value 0 compared to previous. Other numbers remained almost the same. With this information provided by the relative discrepancies technique, despite the very limited number of new records, an audit sample of the previous week's records could be created, namely those starting with the digits 1, 3, 5, or 9. Attempts to build audit samples using only Benford analysis of the cumulative and non-cumulative weekly datasets failed, but the relative discrepancy

technique enabled us to read how the previous week's records affected digit distribution. This analysis was for a weekly period; at last, we deal with analyses of monthly periods.

Figure B3 (Appendix B) illustrates a monthly analysis of the full 2020 dataset. We have Figure B3 (Appendix B) to conduct. We need to determine from these graphs how the previous month's records affected digit distribution. When comparing the end points with their end points from 29.11.2020, almost all digits have the same relative discrepancies except for 1 and 9. It is thus logical to compile an audit sample of records from the previous month that started with 1 or 9. Not only could an audit sample be

successfully built for the monthly dataset, the end result was the same as the result of the Benford analysis.

The weekly and monthly analysis results differ because the records differ. Whereas these results are sometimes difficult to read in the graphs, they can be verified by the discrepancies tables (see Appendix A).

4.3 Comparison of the results

Our aim was to determine audit samples for records from 29.11.2020 to 06.12.2020. To this end, we first resorted to Benford analysis. Using only weekly Benford analysis tests, we can neither obtain meaningful results nor create an audit sample. On the other hand, using the relative discrepancies technique, we could create an audit sample for the related weekly dataset. Moreover, this technique allowed for analyses of both cumulative and non-cumulative data. In the end, the relative discrepancies technique provided a broad perspective, while Benford analysis by itself was not helpful.

Second, we tried to create an audit sample for the dataset that covered the whole of 2020. In the first analysis, we successfully postulated an audit sample for the monthly period using only Benford's Law. In the second analysis, using the relative discrepancies technique, we build an audit sample for just the last month, as well. Both techniques were successful for analysis of a one-month period.

When it comes to the comparison of weekly and monthly periods, it comes down to data size. However, the relative discrepancies technique allows us to use weekly periods and analyze monthly periods, as well, when needed. Thus, using the relative discrepancies technique on a weekly basis and analyzing the results according to the necessary time period is the best option for creating audit samples for continuous auditing.

CHAPTER 5

CONCLUSION

Continuous auditing and Benford's Law are two different methods of conducting auditing. Each has its own strengths and weaknesses. Contemporary auditors benefit from both separately. While there are cases for which their separate use is applicable, the real power of continuous auditing and Benford's Law emerges when they are combined. They compensate for each other's deficiencies.

Today's auditing systems involve more human engagement than necessary and are subject to fraud. With advancements in technology, new auditing tools and methods are emerging that decrease human involvement in the process and minimize the windows for fraud. Whereas continuous auditing is a method that benefits from these new technologies, Benford's Law is one of the oldest auditing methods. Let us explain the purposes of both methods and their pros and cons.

5.1 Discussion of continuous auditing

Continuous auditing is a real-time auditing method. Accounting activities are recorded by computers and reside on servers. On account of this technology, it is possible to access such records online in real time. Computer programs analyze these records algorithmically and produce reports for auditors. This method minimizes human interaction in the analyzing and reporting process. At the same time, publicly sharing real-time records increases trust in the company and optimizes the market for traders. Real-time records decrease the risk for shareholders, traders, and the state, allowing them to take action quickly. Without continuous auditing, records may be published only once, twice, or four times a year depending on the company size. Shareholders,

traders, and the state may receive reports months later, by which point it may be too late to take the necessary actions to prevent losses.

Every tool or method has weaknesses. Despite its many strengths, continuous auditing has a weakness concerning the size of data. Continuous auditing tests the records, but in the end, human auditors analyze the reports produced by a continuous auditing system. Because of the limitations of time and the size of the audit team, a continuous auditing system must create manageable results. This means that samples need to be determined and tested. Currently, Benford's Law remains the best tool for determining audit samples.

5.2 Discussion of Benford's Law

Benford's Law is a mathematical law that enables us to identify potentially inauthentic records – in other words, records possibly created through human intervention.

This mathematical law is a popular tool among auditors for analyzing data quality. As mentioned, this tool analyzes patterns of the distributions of digits in numbers to detect fraud, irregularities, and biases. Auditors observe the distribution of digits in the dataset and compares it to the rates predicted by Benford's. If there exists a significant difference between the two, this is a flag that further analysis of the dataset is necessary.

Human involvement in auditing processes decreases the reliability of the conclusion. This law needs data for analysis, and the data chosen by the company or by the auditor may be corrupt. Benford's Law by itself is therefore insufficient because it neither guarantees the quality of the test data nor can it be used to analyze or report on the data. However, it is the best method of analyzing the authenticity of data.

To expand beyond the authenticity of data, Benford's Law must be supplemented with other tools or methods to guarantee that data has not been changed or deleted. Continuous auditing fills this role and ensures that human access to test data is minimized. Also, continuous auditing systems enable Benford's Law tests of data to be conducted more frequently.

5.3 Our implementation

In our case, we implemented a continuous auditing system for an SME in Turkey, a hotel located in Ankara Turkey. The volume of accounting records was limited, so we tried to determine the best possible technique according to an analysis of several techniques in tandem. We tried to ascertain audit samples using an R script. The question marks in our scenario were the frequency of testing and whether cumulative or non-cumulative data should be used.

In the first test, we applied only Benford analysis to both cumulative and non-cumulative datasets on a monthly and weekly basis. We could determine an audit sample on a weekly basis for neither cumulative nor non-cumulative data. In the case of the cumulative weekly dataset, the volume of records that week was too small to see a difference. For the non-cumulative weekly dataset, the small size of the dataset did not allow Benford analysis to be conducted whatsoever. On the other hand, audit samples were ascertained using monthly cumulative and non-cumulative datasets. The volume of these datasets were sufficient. However, Benford analysis alone does not support time series analysis. We could not determine changes in digit distribution over time using this technique. Also, it is possible for companies to create new accounting records for past dates. Using Benford analysis alone, we cannot analyze these records.

We subsequently used the relative discrepancies technique which enabled us to see how digit distributions deviated from Benford's Law in time. We used cumulative datasets and grouped the records by week. Using this technique, we determined how digit distributions diverged from Benford's Law in time on a weekly basis. The results were clear and allowed the creation of audit samples of weekly and monthly datasets.

In sum, continuous auditing is a real-time, paperless system that minimizes human involvement in the process and maximizes the number of records being audited. But even with continuous auditing, audit samples are needed. Auditors have long used Benford's Law to build their audit samples. Because continuous auditing necessitates time series analysis, we sought a technique that, unlike Benford's Law, would allow analysis over time. Relative discrepancies is a technique that is founded on Benford's Law and allows time series analyses. We implemented the weekly relative discrepancies technique for our SME. Using this technique, we could create weekly or monthly audit samples. This technique also provided us more options for analysis. For our case, using relative discrepancies to analyze weekly cumulative datasets was the best option.

5.4 Market benefit

The quality of auditing determines the quality of knowledge and the market. Companies, shareholders, traders and the state determine their moves according to auditing reports. Proper application of our continuous auditing system may allow these players to make more accurate moves.

Companies benefit from financial reports while building their strategies. The quality of these financial reports is tested in the auditing process. Thus, the quality of

the auditing process directly affects the quality of a company's strategies. Also, auditing systems increase market trust in a company, which in turn increases the volume of the trade of the company's stocks and the assessment of the company's value.

Shareholders judge managers' performance according to financial reports. The quality of these financial reports is tested in the auditing process. The quality of the evaluations of managers thus increases proportional to the quality of auditing. With the application of our proposed system, shareholders would make better decisions, about manager performance. With better-performing managers and more trust in the market, the company's value will go up. This is a direct benefit for shareholders.

In a perfect market, everyone gets the same information at the same time. Because traders trade according to what they know, the timing and quality of the information they receive is crucial. With the proper use of the continuous auditing system, traders get quality, real-time information. Traders and the market thus value companies better. Also, thanks to real-time reporting, traders are freed of the problem of the timeliness of information.

Third-party auditors are licensed by the state to audit companies. States consider licensed auditors' reports to be reliable and behave accordingly. States seek to maximize the possibility of catching fraud while minimizing the risk of fraud in the auditing process itself. The proposed system helps states to regulate the market by providing them with more reliable auditing reports.

5.5 Possible further studies

In this study, we determined the best technique for continuous auditing with Benford's Law for an SME in Turkey. Applying a relative discrepancies technique to cumulative,

weekly datasets turned out to be the best option. We used a one-year dataset for our case study, but because we propose using cumulative data, as the number of years increases so too will the size of the dataset. A ratio between the cumulative dataset size and the number of new records needs to be determined; in time, the volume of new records will be marginal compared to the cumulative dataset. Its effect on digit distribution will become relatively smaller, as well. In further studies, this ratio needs to be determined and the starting date for cumulative datasets may need to be continually updated to obtain meaningful results.

Second, continuous auditing requires advanced cybersecurity. For continuous auditing, auditing firms adopt new technologies that directly access confidential company information. Cybersecurity is thus a significant issue for continuous auditing systems. One actor needs to assume this responsibility and guarantee the safety of firms' data. The continuous auditing process requires software, and it stands to reason that the actor that owns this software, namely the auditors themselves, should be the guarantors. However, auditors as they exist today have no background in cybersecurity or technology. It is not a required skill to obtain the title of auditor (No & Vasarhelyi, 2017). While large auditing firms may develop their own cybersecurity applications, questions remain about whether they need to obtain a second license for these solutions. This problem needs to be solved to be able to broadly implement external continuous auditing solutions. Roles and responsibilities will need to be redefined to some extent.

APPENDIX A

DIGIT DISTRIBUTION TABLES

Table A1. Distribution Table (29.11.2020)

	ratio1	ratio2	ratio3	ratio4	ratio5	ratio6	ratio7	ratio8	ratio9
2020-01-07	0,17	0,11	0,22	0,11	0,11	0,17	0,06	0,00	0,06
2020-01-14	0,17	0,11	0,13	0,15	0,09	0,11	0,09	0,11	0,04
2020-01-21	0,19	0,13	0,14	0,11	0,07	0,10	0,10	0,10	0,06
2020-01-28	0,25	0,12	0,13	0,11	0,07	0,10	0,08	0,07	0,05
2020-02-04	0,22	0,15	0,12	0,12	0,09	0,10	0,09	0,07	0,04
2020-02-11	0,20	0,16	0,14	0,11	0,09	0,09	0,09	0,08	0,04
2020-02-18	0,22	0,16	0,13	0,10	0,09	0,09	0,09	0,08	0,04
2020-02-25	0,23	0,15	0,13	0,11	0,09	0,09	0,09	0,08	0,03
2020-03-03	0,21	0,16	0,12	0,12	0,09	0,08	0,09	0,08	0,04
2020-03-10	0,22	0,15	0,12	0,12	0,09	0,09	0,08	0,09	0,04
2020-03-17	0,23	0,15	0,12	0,12	0,08	0,09	0,08	0,08	0,04
2020-03-24	0,24	0,15	0,12	0,12	0,09	0,09	0,07	0,08	0,04
2020-03-31	0,24	0,14	0,12	0,11	0,10	0,09	0,07	0,08	0,04
2020-04-07	0,24	0,14	0,13	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-14	0,24	0,13	0,12	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-21	0,23	0,14	0,12	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-28	0,24	0,14	0,12	0,11	0,10	0,09	0,07	0,09	0,04
2020-05-05	0,24	0,13	0,12	0,12	0,11	0,09	0,07	0,09	0,04
2020-05-12	0,24	0,14	0,12	0,12	0,10	0,09	0,06	0,08	0,04
2020-05-19	0,25	0,14	0,11	0,12	0,10	0,09	0,06	0,08	0,04
2020-05-26	0,25	0,14	0,12	0,11	0,10	0,08	0,06	0,08	0,04
2020-06-02	0,24	0,14	0,12	0,11	0,11	0,09	0,07	0,08	0,04
2020-06-09	0,24	0,15	0,12	0,11	0,11	0,09	0,07	0,08	0,04
2020-06-16	0,25	0,15	0,12	0,11	0,10	0,08	0,07	0,08	0,04
2020-06-23	0,26	0,15	0,12	0,10	0,10	0,08	0,07	0,08	0,04
2020-06-30	0,25	0,14	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-07	0,25	0,15	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-14	0,26	0,15	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-21	0,26	0,15	0,13	0,10	0,10	0,08	0,05	0,08	0,04
2020-07-28	0,26	0,16	0,12	0,09	0,10	0,08	0,05	0,08	0,04
2020-08-04	0,26	0,15	0,12	0,09	0,10	0,08	0,05	0,08	0,04
2020-08-11	0,26	0,15	0,12	0,09	0,10	0,08	0,06	0,08	0,05

2020-08-18	0,27	0,16	0,12	0,09	0,10	0,08	0,05	0,08	0,05
2020-08-25	0,27	0,16	0,12	0,09	0,09	0,08	0,05	0,08	0,05
2020-09-01	0,26	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05
2020-09-08	0,27	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05
2020-09-15	0,27	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05
2020-09-22	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-09-29	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-06	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-13	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,04
2020-10-20	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-27	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,04
2020-11-03	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-11-10	0,28	0,16	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-11-17	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-11-24	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-12-01	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05

Table A2. Distribution Table (06.12.2020)

	ratio1	ratio2	ratio3	ratio4	ratio5	ratio6	ratio7	ratio8	ratio9
2020-01-07	0,17	0,11	0,22	0,11	0,11	0,17	0,06	0,00	0,06
2020-01-14	0,17	0,11	0,13	0,15	0,09	0,11	0,09	0,11	0,04
2020-01-21	0,19	0,13	0,14	0,11	0,07	0,10	0,10	0,10	0,06
2020-01-28	0,25	0,12	0,13	0,11	0,07	0,10	0,08	0,07	0,05
2020-02-04	0,22	0,15	0,12	0,12	0,09	0,10	0,09	0,07	0,04
2020-02-11	0,20	0,16	0,14	0,11	0,09	0,09	0,09	0,08	0,04
2020-02-18	0,22	0,16	0,13	0,10	0,09	0,09	0,09	0,08	0,04
2020-02-25	0,23	0,15	0,13	0,11	0,09	0,09	0,09	0,08	0,03
2020-03-03	0,21	0,16	0,12	0,12	0,09	0,08	0,09	0,08	0,04
2020-03-10	0,22	0,15	0,12	0,12	0,09	0,09	0,08	0,09	0,04
2020-03-17	0,23	0,15	0,12	0,12	0,08	0,09	0,08	0,08	0,04
2020-03-24	0,24	0,15	0,12	0,12	0,09	0,09	0,07	0,08	0,04
2020-03-31	0,24	0,14	0,12	0,11	0,10	0,09	0,07	0,08	0,04
2020-04-07	0,24	0,14	0,13	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-14	0,24	0,13	0,12	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-21	0,23	0,14	0,12	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-28	0,24	0,14	0,12	0,11	0,10	0,09	0,07	0,09	0,04
2020-05-05	0,24	0,13	0,12	0,12	0,11	0,09	0,07	0,09	0,04
2020-05-12	0,24	0,14	0,12	0,12	0,10	0,09	0,06	0,08	0,04
2020-05-19	0,25	0,14	0,11	0,12	0,10	0,09	0,06	0,08	0,04
2020-05-26	0,25	0,14	0,12	0,11	0,10	0,08	0,06	0,08	0,04
2020-06-02	0,24	0,14	0,12	0,11	0,11	0,09	0,07	0,08	0,04
2020-06-09	0,24	0,15	0,12	0,11	0,11	0,09	0,07	0,08	0,04
2020-06-16	0,25	0,15	0,12	0,11	0,10	0,08	0,07	0,08	0,04
2020-06-23	0,26	0,15	0,12	0,10	0,10	0,08	0,07	0,08	0,04
2020-06-30	0,25	0,14	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-07	0,25	0,15	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-14	0,26	0,15	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-21	0,26	0,15	0,13	0,10	0,10	0,08	0,05	0,08	0,04
2020-07-28	0,26	0,16	0,12	0,09	0,10	0,08	0,05	0,08	0,04
2020-08-04	0,26	0,15	0,12	0,09	0,10	0,08	0,05	0,08	0,04
2020-08-11	0,26	0,15	0,12	0,09	0,10	0,08	0,06	0,08	0,05
2020-08-18	0,27	0,16	0,12	0,09	0,10	0,08	0,05	0,08	0,05
2020-08-25	0,27	0,16	0,12	0,09	0,09	0,08	0,05	0,08	0,05
2020-09-01	0,26	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05
2020-09-08	0,27	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05
2020-09-15	0,27	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05

2020-09-22	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-09-29	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-06	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-13	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,04
2020-10-20	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-27	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,04
2020-11-03	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-11-10	0,28	0,16	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-11-17	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-11-24	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-12-01	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-12-08	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,08	0,05



Table A3. Distribution Table (01.01.2021)

	ratio1	ratio2	ratio3	ratio4	ratio5	ratio6	ratio7	ratio8	ratio9
2020-01-07	0,17	0,11	0,22	0,11	0,11	0,17	0,06	0,00	0,06
2020-01-14	0,17	0,11	0,13	0,15	0,09	0,11	0,09	0,11	0,04
2020-01-21	0,19	0,13	0,14	0,11	0,07	0,10	0,10	0,10	0,06
2020-01-28	0,25	0,12	0,13	0,11	0,07	0,10	0,08	0,07	0,05
2020-02-04	0,22	0,15	0,12	0,12	0,09	0,10	0,09	0,07	0,04
2020-02-11	0,20	0,16	0,14	0,11	0,09	0,09	0,09	0,08	0,04
2020-02-18	0,22	0,16	0,13	0,10	0,09	0,09	0,09	0,08	0,04
2020-02-25	0,23	0,15	0,13	0,11	0,09	0,09	0,09	0,08	0,03
2020-03-03	0,21	0,16	0,12	0,12	0,09	0,08	0,09	0,08	0,04
2020-03-10	0,22	0,15	0,12	0,12	0,09	0,09	0,08	0,09	0,04
2020-03-17	0,23	0,15	0,12	0,12	0,08	0,09	0,08	0,08	0,04
2020-03-24	0,24	0,15	0,12	0,12	0,09	0,09	0,07	0,08	0,04
2020-03-31	0,24	0,14	0,12	0,11	0,10	0,09	0,07	0,08	0,04
2020-04-07	0,24	0,14	0,13	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-14	0,24	0,13	0,12	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-21	0,23	0,14	0,12	0,12	0,10	0,09	0,07	0,08	0,04
2020-04-28	0,24	0,14	0,12	0,11	0,10	0,09	0,07	0,09	0,04
2020-05-05	0,24	0,13	0,12	0,12	0,11	0,09	0,07	0,09	0,04
2020-05-12	0,24	0,14	0,12	0,12	0,10	0,09	0,06	0,08	0,04
2020-05-19	0,25	0,14	0,11	0,12	0,10	0,09	0,06	0,08	0,04
2020-05-26	0,25	0,14	0,12	0,11	0,10	0,08	0,06	0,08	0,04
2020-06-02	0,24	0,14	0,12	0,11	0,11	0,09	0,07	0,08	0,04
2020-06-09	0,24	0,15	0,12	0,11	0,11	0,09	0,07	0,08	0,04
2020-06-16	0,25	0,15	0,12	0,11	0,10	0,08	0,07	0,08	0,04
2020-06-23	0,26	0,15	0,12	0,10	0,10	0,08	0,07	0,08	0,04
2020-06-30	0,25	0,14	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-07	0,25	0,15	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-14	0,26	0,15	0,12	0,10	0,10	0,08	0,06	0,08	0,04
2020-07-21	0,26	0,15	0,13	0,10	0,10	0,08	0,05	0,08	0,04
2020-07-28	0,26	0,16	0,12	0,09	0,10	0,08	0,05	0,08	0,04
2020-08-04	0,26	0,15	0,12	0,09	0,10	0,08	0,05	0,08	0,04
2020-08-11	0,26	0,15	0,12	0,09	0,10	0,08	0,06	0,08	0,05
2020-08-18	0,27	0,16	0,12	0,09	0,10	0,08	0,05	0,08	0,05
2020-08-25	0,27	0,16	0,12	0,09	0,09	0,08	0,05	0,08	0,05
2020-09-01	0,26	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05
2020-09-08	0,27	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05
2020-09-15	0,27	0,15	0,12	0,09	0,09	0,08	0,06	0,08	0,05

2020-09-22	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-09-29	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-06	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-13	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,04
2020-10-20	0,27	0,16	0,13	0,09	0,09	0,07	0,06	0,08	0,05
2020-10-27	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,04
2020-11-03	0,27	0,16	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-11-10	0,28	0,16	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-11-17	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-11-24	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-12-01	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-12-08	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-12-15	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,08	0,05
2020-12-22	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05
2020-12-29	0,27	0,17	0,12	0,09	0,09	0,07	0,06	0,07	0,05

Table A4. Discrepancies Table (29.11.2020)

	disc1	disc2	disc3	disc4	disc5	disc6	disc7	disc8	disc9
2020-01-07	-0,45	-0,37	0,78	0,15	0,40	1,49	-0,04	-1,00	0,21
2020-01-14	-0,42	-0,38	0,04	0,57	0,10	0,62	0,50	1,12	-0,05
2020-01-21	-0,38	-0,27	0,14	0,18	-0,10	0,49	0,72	0,95	0,25
2020-01-28	-0,18	-0,30	0,07	0,17	-0,09	0,54	0,42	0,41	0,13
2020-02-04	-0,27	-0,17	-0,07	0,21	0,11	0,53	0,64	0,43	-0,04
2020-02-11	-0,34	-0,08	0,09	0,09	0,10	0,39	0,61	0,58	-0,05
2020-02-18	-0,27	-0,06	0,06	0,02	0,11	0,31	0,52	0,61	-0,16
2020-02-25	-0,23	-0,14	0,02	0,16	0,11	0,32	0,52	0,53	-0,25
2020-03-03	-0,29	-0,12	-0,02	0,26	0,17	0,19	0,52	0,64	-0,08
2020-03-10	-0,25	-0,14	-0,01	0,24	0,13	0,27	0,40	0,67	-0,15
2020-03-17	-0,24	-0,12	-0,03	0,25	0,07	0,37	0,33	0,65	-0,20
2020-03-24	-0,21	-0,15	-0,03	0,21	0,08	0,38	0,29	0,60	-0,14
2020-03-31	-0,21	-0,18	-0,01	0,17	0,22	0,35	0,27	0,63	-0,20
2020-04-07	-0,22	-0,21	0,01	0,20	0,26	0,30	0,22	0,64	-0,08
2020-04-14	-0,21	-0,24	-0,02	0,23	0,26	0,31	0,24	0,65	-0,11
2020-04-21	-0,22	-0,21	-0,05	0,19	0,30	0,31	0,20	0,66	-0,07
2020-04-28	-0,21	-0,21	-0,05	0,16	0,27	0,33	0,18	0,68	-0,09
2020-05-05	-0,19	-0,26	-0,05	0,20	0,36	0,28	0,15	0,68	-0,15
2020-05-12	-0,19	-0,23	-0,06	0,24	0,31	0,27	0,10	0,62	-0,13
2020-05-19	-0,16	-0,23	-0,09	0,21	0,31	0,28	0,12	0,57	-0,15
2020-05-26	-0,18	-0,22	-0,01	0,18	0,31	0,25	0,09	0,53	-0,11
2020-06-02	-0,20	-0,18	-0,05	0,13	0,36	0,29	0,13	0,55	-0,13
2020-06-09	-0,19	-0,15	-0,06	0,12	0,34	0,28	0,13	0,50	-0,16
2020-06-16	-0,16	-0,16	-0,04	0,10	0,32	0,23	0,12	0,53	-0,19
2020-06-23	-0,15	-0,16	-0,01	0,06	0,25	0,26	0,14	0,49	-0,19
2020-06-30	-0,16	-0,19	-0,02	0,06	0,33	0,25	0,05	0,57	-0,04
2020-07-07	-0,17	-0,16	-0,02	0,02	0,32	0,27	0,00	0,62	-0,05
2020-07-14	-0,15	-0,16	-0,01	0,05	0,28	0,24	-0,05	0,55	-0,02
2020-07-21	-0,14	-0,14	0,01	0,00	0,22	0,20	-0,07	0,60	-0,03
2020-07-28	-0,13	-0,11	-0,02	-0,04	0,20	0,23	-0,10	0,58	-0,03
2020-08-04	-0,12	-0,13	0,00	-0,04	0,23	0,23	-0,08	0,54	-0,04
2020-08-11	-0,13	-0,12	-0,02	-0,06	0,22	0,22	-0,04	0,54	0,02
2020-08-18	-0,11	-0,11	-0,04	-0,09	0,21	0,18	-0,05	0,54	0,05
2020-08-25	-0,10	-0,10	-0,04	-0,11	0,19	0,15	-0,06	0,58	0,02
2020-09-01	-0,12	-0,13	-0,02	-0,02	0,18	0,16	-0,03	0,59	0,03
2020-09-08	-0,12	-0,15	-0,02	-0,05	0,19	0,15	0,02	0,58	0,04
2020-09-15	-0,11	-0,12	-0,01	-0,06	0,16	0,14	-0,01	0,57	0,01

2020-09-22	-0,11	-0,12	0,00	-0,07	0,13	0,12	-0,01	0,58	0,04
2020-09-29	-0,10	-0,11	-0,01	-0,06	0,10	0,11	0,01	0,61	0,02
2020-10-06	-0,12	-0,11	0,00	-0,04	0,10	0,11	0,08	0,61	-0,01
2020-10-13	-0,09	-0,11	0,01	-0,05	0,09	0,07	0,05	0,56	-0,02
2020-10-20	-0,10	-0,09	0,01	-0,06	0,09	0,05	0,03	0,55	-0,01
2020-10-27	-0,10	-0,08	-0,01	-0,06	0,08	0,06	0,07	0,53	-0,02
2020-11-03	-0,10	-0,08	-0,03	-0,07	0,14	0,07	0,06	0,48	0,00
2020-11-10	-0,09	-0,07	-0,04	-0,09	0,13	0,06	0,05	0,45	0,02
2020-11-17	-0,09	-0,05	-0,05	-0,08	0,13	0,05	0,06	0,45	0,03
2020-11-24	-0,09	-0,05	-0,07	-0,08	0,12	0,08	0,04	0,47	0,04
2020-12-01	-0,10	-0,05	-0,07	-0,06	0,13	0,06	0,01	0,45	0,09



Table A5. Discrepancies Table (06.12.2020)

	disc1	disc2	disc3	disc4	disc5	disc6	disc7	disc8	disc9
2020-01-07	-0,45	-0,37	0,78	0,15	0,40	1,49	-0,04	-1,00	0,21
2020-01-14	-0,42	-0,38	0,04	0,57	0,10	0,62	0,50	1,12	-0,05
2020-01-21	-0,38	-0,27	0,14	0,18	-0,10	0,49	0,72	0,95	0,25
2020-01-28	-0,18	-0,30	0,07	0,17	-0,09	0,54	0,42	0,41	0,13
2020-02-04	-0,27	-0,17	-0,07	0,21	0,11	0,53	0,64	0,43	-0,04
2020-02-11	-0,34	-0,08	0,09	0,09	0,10	0,39	0,61	0,58	-0,05
2020-02-18	-0,27	-0,06	0,06	0,02	0,11	0,31	0,52	0,61	-0,16
2020-02-25	-0,23	-0,14	0,02	0,16	0,11	0,32	0,52	0,53	-0,25
2020-03-03	-0,29	-0,12	-0,02	0,26	0,17	0,19	0,52	0,64	-0,08
2020-03-10	-0,25	-0,14	-0,01	0,24	0,13	0,27	0,40	0,67	-0,15
2020-03-17	-0,24	-0,12	-0,03	0,25	0,07	0,37	0,33	0,65	-0,20
2020-03-24	-0,21	-0,15	-0,03	0,21	0,08	0,38	0,29	0,60	-0,14
2020-03-31	-0,21	-0,18	-0,01	0,17	0,22	0,35	0,27	0,63	-0,20
2020-04-07	-0,22	-0,21	0,01	0,20	0,26	0,30	0,22	0,64	-0,08
2020-04-14	-0,21	-0,24	-0,02	0,23	0,26	0,31	0,24	0,65	-0,11
2020-04-21	-0,22	-0,21	-0,05	0,19	0,30	0,31	0,20	0,66	-0,07
2020-04-28	-0,21	-0,21	-0,05	0,16	0,27	0,33	0,18	0,68	-0,09
2020-05-05	-0,19	-0,26	-0,05	0,20	0,36	0,28	0,15	0,68	-0,15
2020-05-12	-0,19	-0,23	-0,06	0,24	0,31	0,27	0,10	0,62	-0,13
2020-05-19	-0,16	-0,23	-0,09	0,21	0,31	0,28	0,12	0,57	-0,15
2020-05-26	-0,18	-0,22	-0,01	0,18	0,31	0,25	0,09	0,53	-0,11
2020-06-02	-0,20	-0,18	-0,05	0,13	0,36	0,29	0,13	0,55	-0,13
2020-06-09	-0,19	-0,15	-0,06	0,12	0,34	0,28	0,13	0,50	-0,16
2020-06-16	-0,16	-0,16	-0,04	0,10	0,32	0,23	0,12	0,53	-0,19
2020-06-23	-0,15	-0,16	-0,01	0,06	0,25	0,26	0,14	0,49	-0,19
2020-06-30	-0,16	-0,19	-0,02	0,06	0,33	0,25	0,05	0,57	-0,04
2020-07-07	-0,17	-0,16	-0,02	0,02	0,32	0,27	0,00	0,62	-0,05
2020-07-14	-0,15	-0,16	-0,01	0,05	0,28	0,24	-0,05	0,55	-0,02
2020-07-21	-0,14	-0,14	0,01	0,00	0,22	0,20	-0,07	0,60	-0,03
2020-07-28	-0,13	-0,11	-0,02	-0,04	0,20	0,23	-0,10	0,58	-0,03
2020-08-04	-0,12	-0,13	0,00	-0,04	0,23	0,23	-0,08	0,54	-0,04
2020-08-11	-0,13	-0,12	-0,02	-0,06	0,22	0,22	-0,04	0,54	0,02
2020-08-18	-0,11	-0,11	-0,04	-0,09	0,21	0,18	-0,05	0,54	0,05
2020-08-25	-0,10	-0,10	-0,04	-0,11	0,19	0,15	-0,06	0,58	0,02
2020-09-01	-0,12	-0,13	-0,02	-0,02	0,18	0,16	-0,03	0,59	0,03
2020-09-08	-0,12	-0,15	-0,02	-0,05	0,19	0,15	0,02	0,58	0,04
2020-09-15	-0,11	-0,12	-0,01	-0,06	0,16	0,14	-0,01	0,57	0,01

2020-09-22	-0,11	-0,12	0,00	-0,07	0,13	0,12	-0,01	0,58	0,04
2020-09-29	-0,10	-0,11	-0,01	-0,06	0,10	0,11	0,01	0,61	0,02
2020-10-06	-0,12	-0,11	0,00	-0,04	0,10	0,11	0,08	0,61	-0,01
2020-10-13	-0,09	-0,11	0,01	-0,05	0,09	0,07	0,05	0,56	-0,02
2020-10-20	-0,10	-0,09	0,01	-0,06	0,09	0,05	0,03	0,55	-0,01
2020-10-27	-0,10	-0,08	-0,01	-0,06	0,08	0,06	0,07	0,53	-0,02
2020-11-03	-0,10	-0,08	-0,03	-0,07	0,14	0,07	0,06	0,48	0,00
2020-11-10	-0,09	-0,07	-0,04	-0,09	0,13	0,06	0,05	0,45	0,02
2020-11-17	-0,09	-0,05	-0,05	-0,08	0,13	0,05	0,06	0,45	0,03
2020-11-24	-0,09	-0,05	-0,07	-0,08	0,12	0,08	0,04	0,47	0,04
2020-12-01	-0,11	-0,03	-0,07	-0,06	0,15	0,06	0,02	0,45	0,10
2020-12-08	-0,11	-0,04	-0,07	-0,07	0,15	0,05	0,01	0,47	0,13



Table A6. Discrepancies Table (01.01.2021)

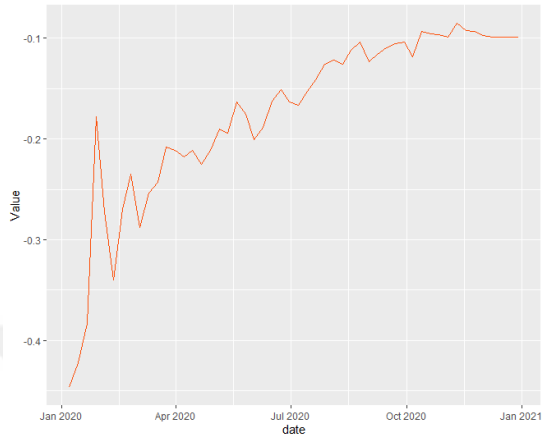
	disc1	disc2	disc3	disc4	disc5	disc6	disc7	disc8	disc9
2020-01-07	-0,45	-0,37	0,78	0,15	0,40	1,49	-0,04	-1,00	0,21
2020-01-14	-0,42	-0,38	0,04	0,57	0,10	0,62	0,50	1,12	-0,05
2020-01-21	-0,38	-0,27	0,14	0,18	-0,10	0,49	0,72	0,95	0,25
2020-01-28	-0,18	-0,30	0,07	0,17	-0,09	0,54	0,42	0,41	0,13
2020-02-04	-0,27	-0,17	-0,07	0,21	0,11	0,53	0,64	0,43	-0,04
2020-02-11	-0,34	-0,08	0,09	0,09	0,10	0,39	0,61	0,58	-0,05
2020-02-18	-0,27	-0,06	0,06	0,02	0,11	0,31	0,52	0,61	-0,16
2020-02-25	-0,23	-0,14	0,02	0,16	0,11	0,32	0,52	0,53	-0,25
2020-03-03	-0,29	-0,12	-0,02	0,26	0,17	0,19	0,52	0,64	-0,08
2020-03-10	-0,25	-0,14	-0,01	0,24	0,13	0,27	0,40	0,67	-0,15
2020-03-17	-0,24	-0,12	-0,03	0,25	0,07	0,37	0,33	0,65	-0,20
2020-03-24	-0,21	-0,15	-0,03	0,21	0,08	0,38	0,29	0,60	-0,14
2020-03-31	-0,21	-0,18	-0,01	0,17	0,22	0,35	0,27	0,63	-0,20
2020-04-07	-0,22	-0,21	0,01	0,20	0,26	0,30	0,22	0,64	-0,08
2020-04-14	-0,21	-0,24	-0,02	0,23	0,26	0,31	0,24	0,65	-0,11
2020-04-21	-0,22	-0,21	-0,05	0,19	0,30	0,31	0,20	0,66	-0,07
2020-04-28	-0,21	-0,21	-0,05	0,16	0,27	0,33	0,18	0,68	-0,09
2020-05-05	-0,19	-0,26	-0,05	0,20	0,36	0,28	0,15	0,68	-0,15
2020-05-12	-0,19	-0,23	-0,06	0,24	0,31	0,27	0,10	0,62	-0,13
2020-05-19	-0,16	-0,23	-0,09	0,21	0,31	0,28	0,12	0,57	-0,15
2020-05-26	-0,18	-0,22	-0,01	0,18	0,31	0,25	0,09	0,53	-0,11
2020-06-02	-0,20	-0,18	-0,05	0,13	0,36	0,29	0,13	0,55	-0,13
2020-06-09	-0,19	-0,15	-0,06	0,12	0,34	0,28	0,13	0,50	-0,16
2020-06-16	-0,16	-0,16	-0,04	0,10	0,32	0,23	0,12	0,53	-0,19
2020-06-23	-0,15	-0,16	-0,01	0,06	0,25	0,26	0,14	0,49	-0,19
2020-06-30	-0,16	-0,19	-0,02	0,06	0,33	0,25	0,05	0,57	-0,04
2020-07-07	-0,17	-0,16	-0,02	0,02	0,32	0,27	0,00	0,62	-0,05
2020-07-14	-0,15	-0,16	-0,01	0,05	0,28	0,24	-0,05	0,55	-0,02
2020-07-21	-0,14	-0,14	0,01	0,00	0,22	0,20	-0,07	0,60	-0,03
2020-07-28	-0,13	-0,11	-0,02	-0,04	0,20	0,23	-0,10	0,58	-0,03
2020-08-04	-0,12	-0,13	0,00	-0,04	0,23	0,23	-0,08	0,54	-0,04
2020-08-11	-0,13	-0,12	-0,02	-0,06	0,22	0,22	-0,04	0,54	0,02
2020-08-18	-0,11	-0,11	-0,04	-0,09	0,21	0,18	-0,05	0,54	0,05
2020-08-25	-0,10	-0,10	-0,04	-0,11	0,19	0,15	-0,06	0,58	0,02
2020-09-01	-0,12	-0,13	-0,02	-0,02	0,18	0,16	-0,03	0,59	0,03
2020-09-08	-0,12	-0,15	-0,02	-0,05	0,19	0,15	0,02	0,58	0,04
2020-09-15	-0,11	-0,12	-0,01	-0,06	0,16	0,14	-0,01	0,57	0,01

2020-09-22	-0,11	-0,12	0,00	-0,07	0,13	0,12	-0,01	0,58	0,04
2020-09-29	-0,10	-0,11	-0,01	-0,06	0,10	0,11	0,01	0,61	0,02
2020-10-06	-0,12	-0,11	0,00	-0,04	0,10	0,11	0,08	0,61	-0,01
2020-10-13	-0,09	-0,11	0,01	-0,05	0,09	0,07	0,05	0,56	-0,02
2020-10-20	-0,10	-0,09	0,01	-0,06	0,09	0,05	0,03	0,55	-0,01
2020-10-27	-0,10	-0,08	-0,01	-0,06	0,08	0,06	0,07	0,53	-0,02
2020-11-03	-0,10	-0,08	-0,03	-0,07	0,14	0,07	0,06	0,48	0,00
2020-11-10	-0,09	-0,07	-0,04	-0,09	0,13	0,06	0,05	0,45	0,02
2020-11-17	-0,09	-0,05	-0,05	-0,08	0,13	0,05	0,06	0,45	0,03
2020-11-24	-0,09	-0,05	-0,07	-0,08	0,12	0,08	0,04	0,47	0,04
2020-12-01	-0,11	-0,03	-0,07	-0,06	0,15	0,06	0,02	0,45	0,10
2020-12-08	-0,11	-0,04	-0,07	-0,07	0,15	0,05	0,01	0,47	0,13
2020-12-15	-0,10	-0,04	-0,06	-0,09	0,15	0,05	-0,02	0,48	0,17
2020-12-22	-0,10	-0,04	-0,06	-0,09	0,13	0,03	0,04	0,45	0,19
2020-12-29	-0,11	-0,04	-0,07	-0,07	0,12	0,06	0,04	0,44	0,18

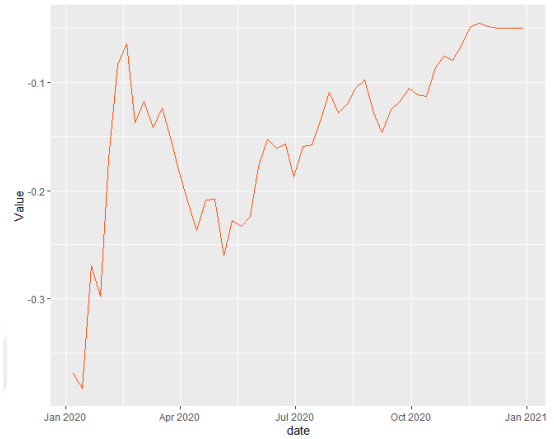
APPENDIX B

RELATIVE DISCREPANCIES TEST RESULTS

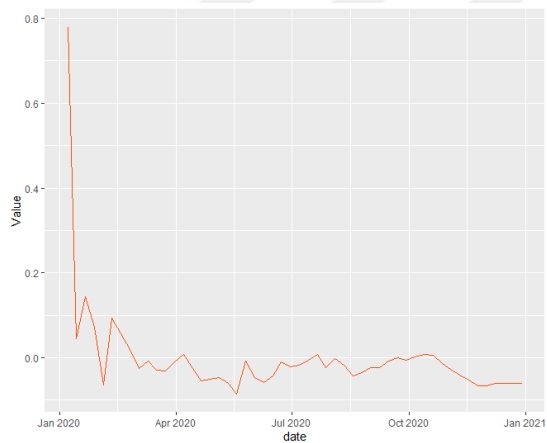
Starting with 1



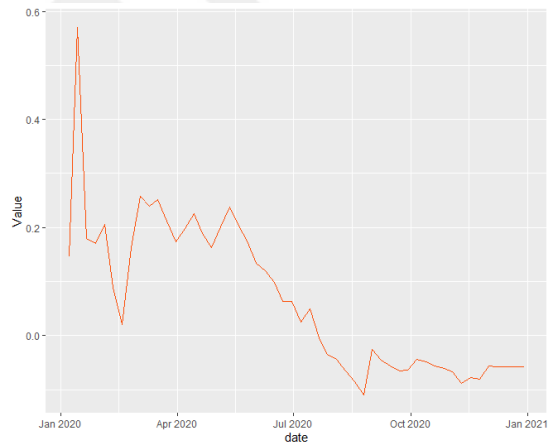
Starting with 2



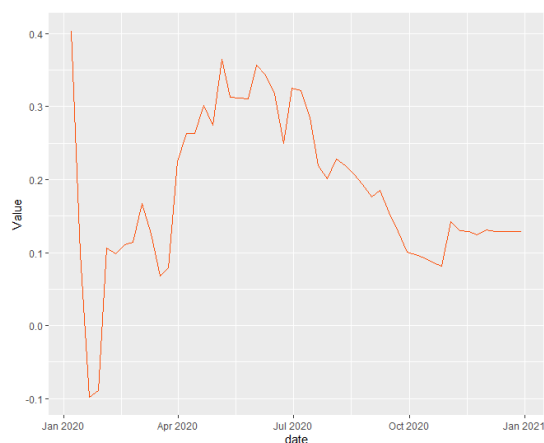
Starting with 3



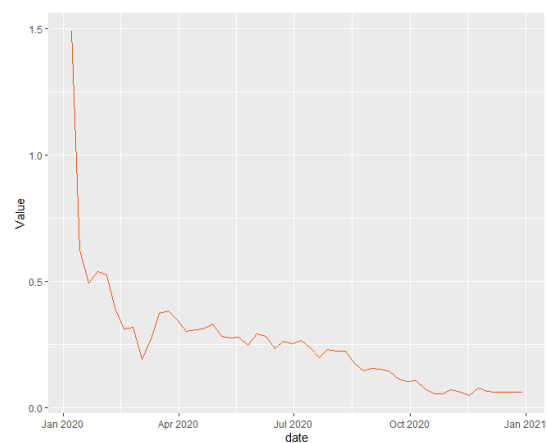
Starting with 4



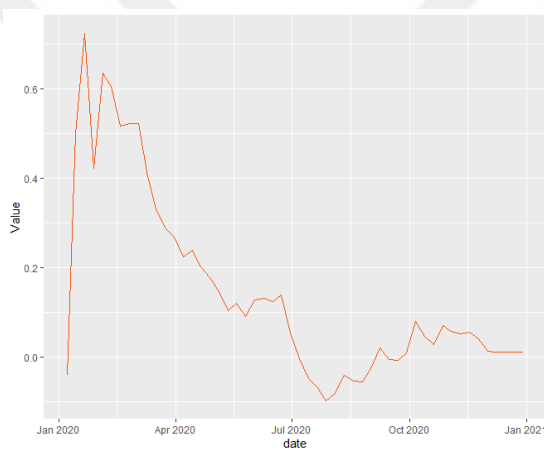
Starting with 5



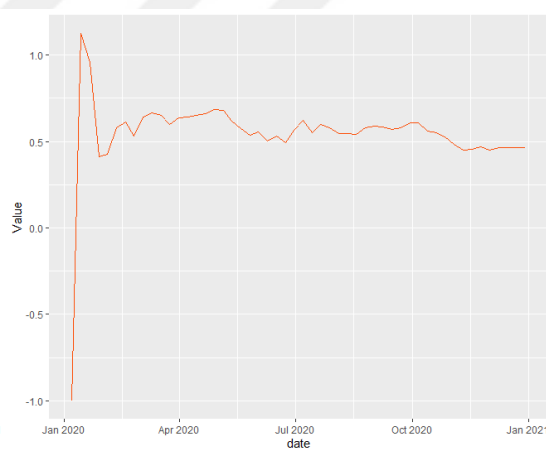
Starting with 6



Starting with 7



Starting with 8



Starting with 9

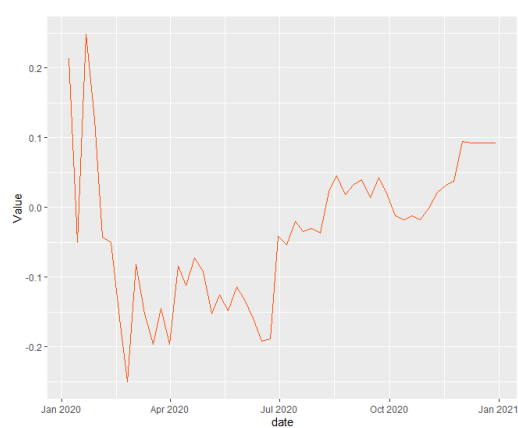
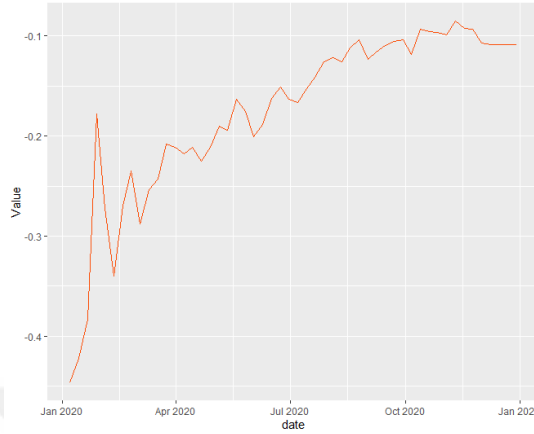
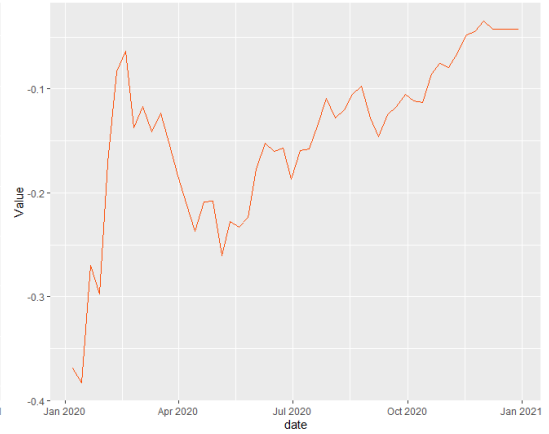


Figure B1. Relative discrepancies up to 29.11.2020

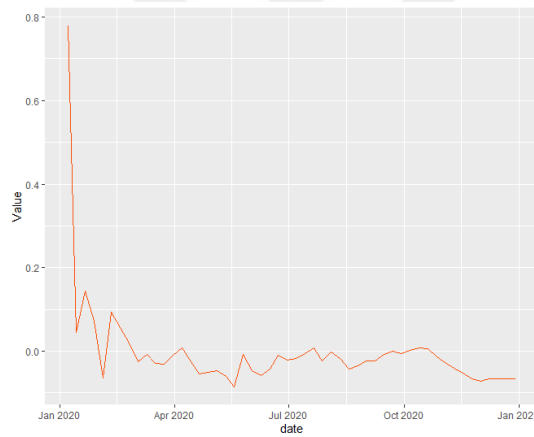
Starting with 1



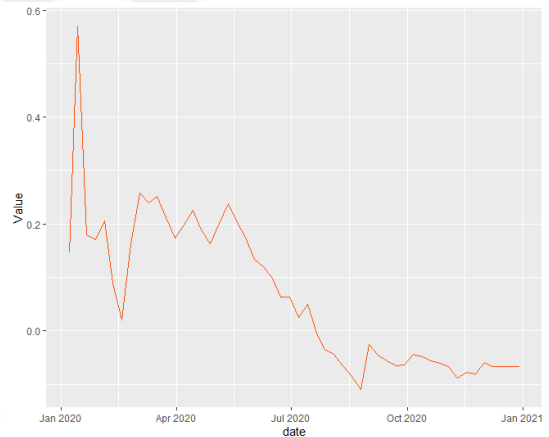
Starting with 2



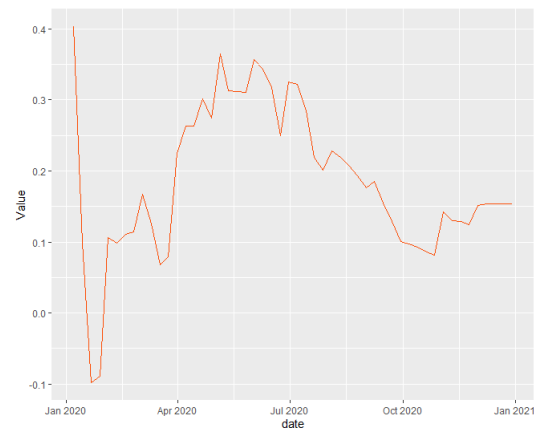
Starting with 3



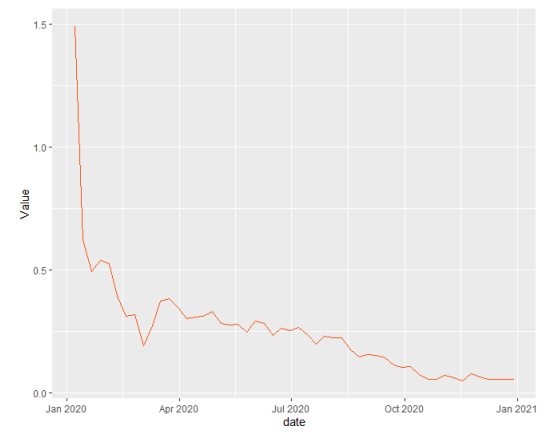
Starting with 4



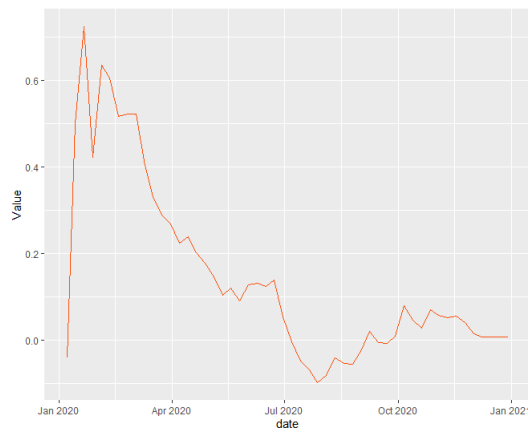
Starting with 5



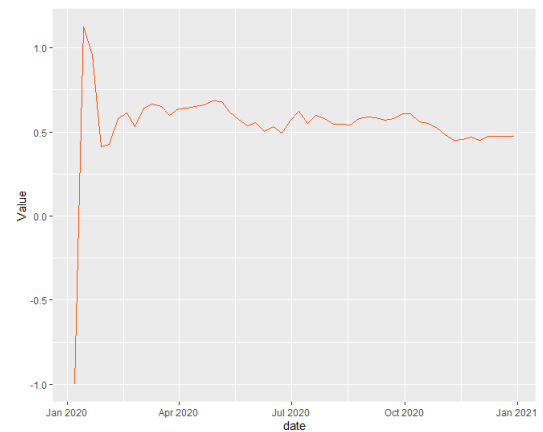
Starting with 6



Starting with 7



Starting with 8



Starting with 9

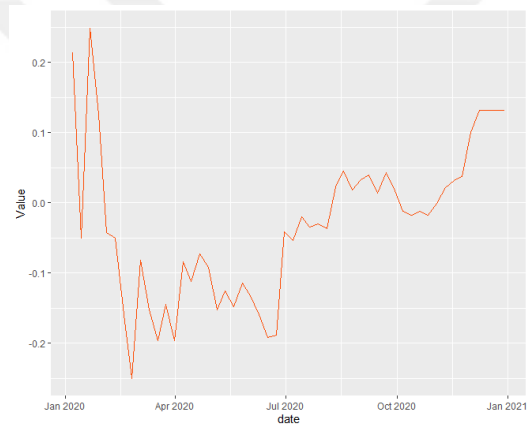
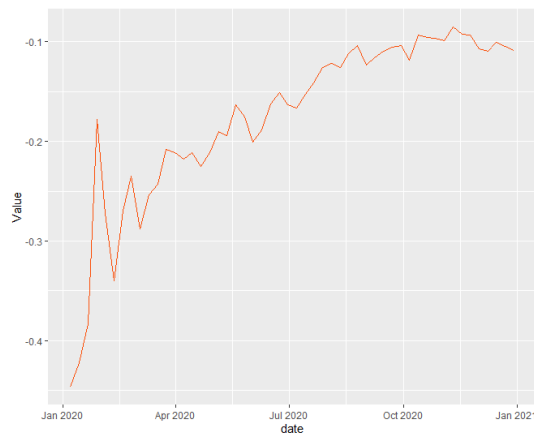
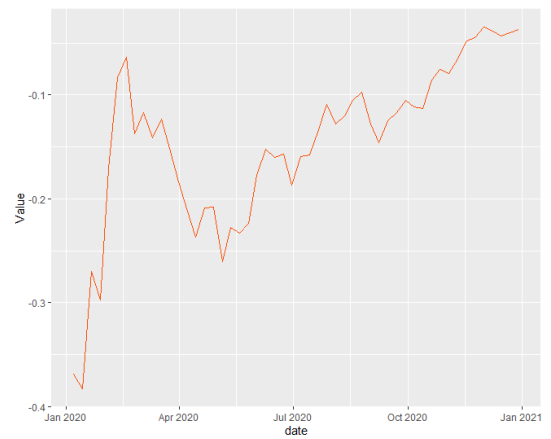


Figure B2. Relative discrepancies up to 06.12.2020

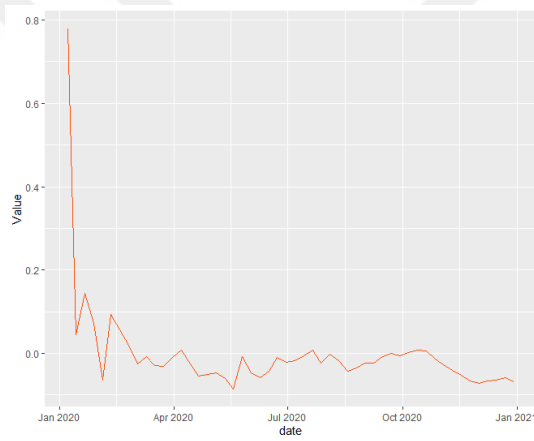
Starting with 1



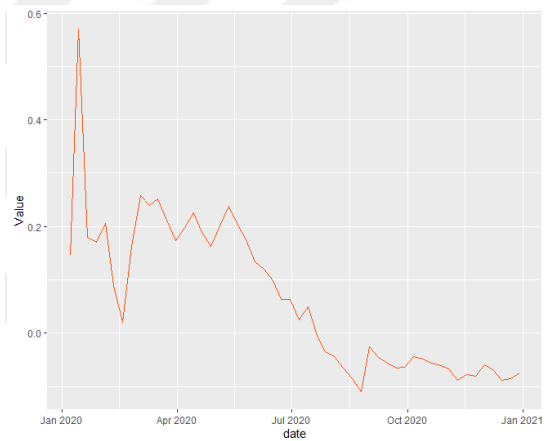
Starting with 2



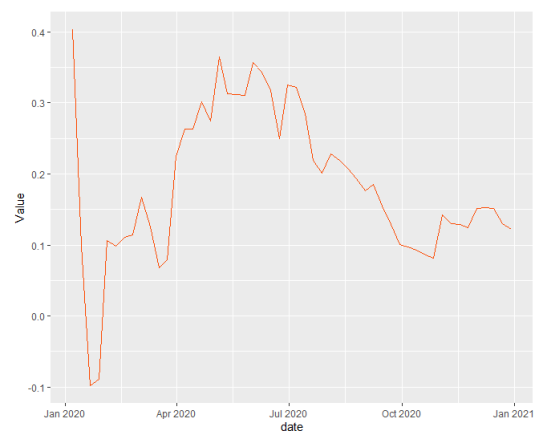
Starting with 3



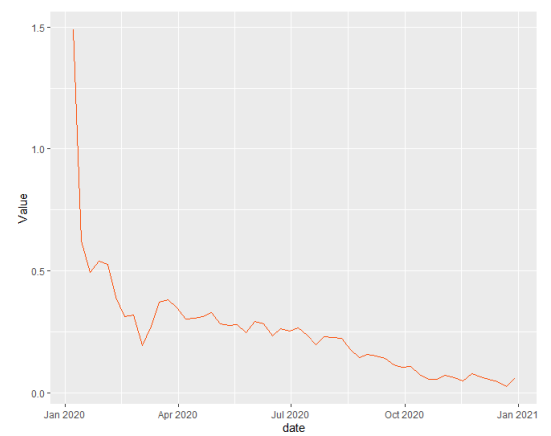
Starting with 4



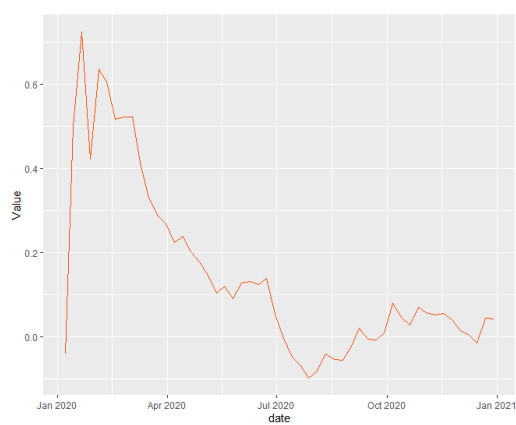
Starting with 5



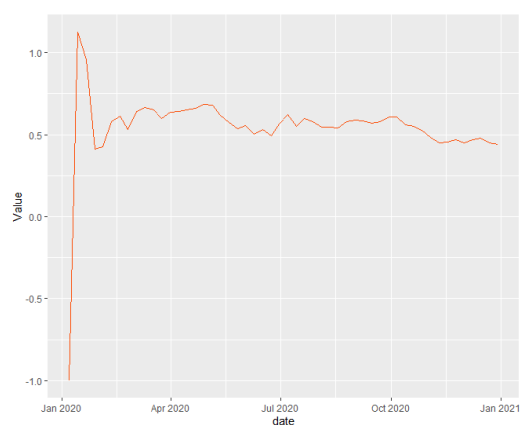
Starting with 6



Starting with 7



Starting with 8



Starting with 9

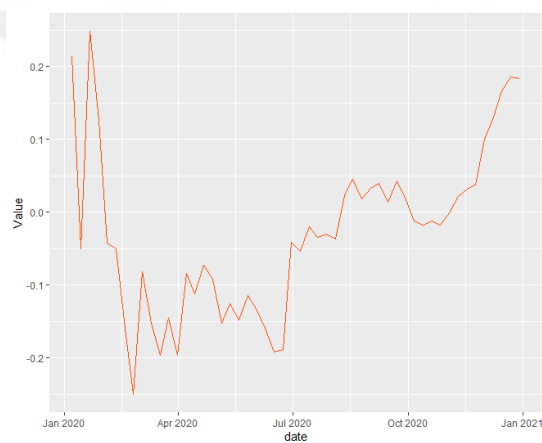


Figure B3. Relative discrepancies up to 01.01.2020

APPENDIX C

R SCRIPT

```
library(benford.analysis)
library(openxlsx)
library(ggplot2)
library(sqldf)

#Data Source
data <- sqldf("*****")
#View(data)

#Define report path
sfilename <- "*****"

#define first digit
data$firstdigit <- substr(data$Cikis_Tutar,1,1)

data$dateformat <-
paste(substr(data$Tarih,7,10),substr(data$Tarih,4,5),substr(data$Tarih,1,2),sep = "-")
data$date <-
paste0(substr(data$Tarih,7,10),substr(data$Tarih,4,5),substr(data$Tarih,1,2))
data$date <- as.integer(data$date)

return2 <- seq(as.Date('2020-01-01'), as.Date('2020-12-31'), by = 'days')
return2 <- as.data.frame(return2)
return2$datenumber <-
paste0(substr(return2$return2,1,4),substr(return2$return2,6,7),substr(return2$return2
,9,10))
return2$datenumber <- as.integer(return2$datenumber)

#Total Count
return2$totalcount <-0
return2$totalcount <-as.integer(return2$totalcount)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c)
    {
      for (t in 1:nrow(return2))
      {
```

```

        if(return2$datenumber[t]==c)
        {v <-return2$totalcount[t]
        v=v+1
        return2$totalcount[t]=v }
    }
  }}
}

#1
return2$count1 <-0
return2$count1 <-as.integer(return2$count1)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c & data$firstdigit[i]=="1")
    {
      for (t in 1:nrow(return2))
      {
        if(return2$datenumber[t]==c)
        {v <-return2$count1[t]
        v=v+1
        return2$count1[t]=v }
      }
    }
  }
}

#2
return2$count2 <-0
return2$count2 <-as.integer(return2$count2)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c & data$firstdigit[i]=="2")
    {
      for (t in 1:nrow(return2))
      {
        if(return2$datenumber[t]==c)
        {v <-return2$count2[t]
        v=v+1

```

```

        return2$count2[t]=v }
    }
}
}
}

#3
return2$count3 <-0
return2$count3 <-as.integer(return2$count3)
v=0
a=0
for (b in 1:52)
{
    a=b*7
    c <- return2$datenummer[a]
    for (i in 1:nrow(data))
    {
        if(data$date[i]<=c & data$firstdigit[i]=="3")
        {
            for (t in 1:nrow(return2))
            {
                if(return2$datenummer[t]==c)
                {v <-return2$count3[t]
                v=v+1
                return2$count3[t]=v }
            }
        }
    }
}

```

```

#4
return2$count4 <-0
return2$count4 <-as.integer(return2$count4)
v=0
a=0
for (b in 1:52)
{
    a=b*7
    c <- return2$datenummer[a]
    for (i in 1:nrow(data))
    {
        if(data$date[i]<=c & data$firstdigit[i]=="4")
        {
            for (t in 1:nrow(return2))
            {
                if(return2$datenummer[t]==c)
                {v <-return2$count4[t]
                v=v+1
                return2$count4[t]=v }
            }
        }
    }
}

```

```

    }
  }
}

#5
return2$count5 <-0
return2$count5 <-as.integer(return2$count5)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c & data$firstdigit[i]=="5")
    {
      for (t in 1:nrow(return2))
      {
        if(return2$datenumber[t]==c)
        {v <-return2$count5[t]
        v=v+1
        return2$count5[t]=v }
      }
    }
  }
}

```

```

#6
return2$count6 <-0
return2$count6 <-as.integer(return2$count6)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c & data$firstdigit[i]=="6")
    {
      for (t in 1:nrow(return2))
      {
        if(return2$datenumber[t]==c)
        {v <-return2$count6[t]
        v=v+1
        return2$count6[t]=v }
      }
    }
  }
}

```

```

}

#7
return2$count7 <-0
return2$count7 <-as.integer(return2$count7)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c & data$firstdigit[i]=="7")
    {
      for (t in 1:nrow(return2))
      {
        if(return2$datenumber[t]==c)
        {v <-return2$count7[t]
        v=v+1
        return2$count7[t]=v }
      }
    }
  }
}

```

```

#8
return2$count8 <-0
return2$count8 <-as.integer(return2$count8)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c & data$firstdigit[i]=="8")
    {
      for (t in 1:nrow(return2))
      {
        if(return2$datenumber[t]==c)
        {v <-return2$count8[t]
        v=v+1
        return2$count8[t]=v }
      }
    }
  }
}

```

```

#9
return2$count9 <-0
return2$count9 <-as.integer(return2$count9)
v=0
a=0
for (b in 1:52)
{
  a=b*7
  c <- return2$datenumber[a]
  for (i in 1:nrow(data))
  {
    if(data$date[i]<=c & data$firstdigit[i]=="9")
    {
      for (t in 1:nrow(return2))
      {
        if(return2$datenumber[t]==c)
        {v <-return2$count9[t]
        v=v+1
        return2$count9[t]=v }
      }
    }
  }
}

#Calculate distributions
for (i in 1:nrow(return2))
{
  return2$ratio1[i]<- return2$count1[i]/return2$totalcount[i]
  return2$ratio2[i]<- return2$count2[i]/return2$totalcount[i]
  return2$ratio3[i]<- return2$count3[i]/return2$totalcount[i]
  return2$ratio4[i]<- return2$count4[i]/return2$totalcount[i]
  return2$ratio5[i]<- return2$count5[i]/return2$totalcount[i]
  return2$ratio6[i]<- return2$count6[i]/return2$totalcount[i]
  return2$ratio7[i]<- return2$count7[i]/return2$totalcount[i]
  return2$ratio8[i]<- return2$count8[i]/return2$totalcount[i]
  return2$ratio9[i]<- return2$count9[i]/return2$totalcount[i]
}

#Delete total0 rows
return2<-return2[!(return2$totalcount==0),]

#Define Expected distribution rates according to Benford's law

expratio1 = 0.30103
expratio2 = 0.176091
expratio3 = 0.124939
expratio4 = 0.096910
expratio5 = 0.079181
expratio6 = 0.066947

```

```

expratio7 = 0.057992
expratio8 = 0.051153
expratio9 = 0.045757

#calculate discrepancies
for (i in 1:nrow(return2))
{
  return2$discrepancies1[i]<- (return2$ratio1[i]-expratio1)/expratio1
  return2$discrepancies2[i]<- (return2$ratio2[i]-expratio2)/expratio2
  return2$discrepancies3[i]<- (return2$ratio3[i]-expratio3)/expratio3
  return2$discrepancies4[i]<- (return2$ratio4[i]-expratio4)/expratio4
  return2$discrepancies5[i]<- (return2$ratio5[i]-expratio5)/expratio5
  return2$discrepancies6[i]<- (return2$ratio6[i]-expratio6)/expratio6
  return2$discrepancies7[i]<- (return2$ratio7[i]-expratio7)/expratio7
  return2$discrepancies8[i]<- (return2$ratio8[i]-expratio8)/expratio8
  return2$discrepancies9[i]<- (return2$ratio9[i]-expratio9)/expratio9
}

#Define row names
row.names(return2) <- return2$return2

#Define distribution table tables
distributiontable <- return2
distributiontable[1:12] <-NULL
distributiontable[10:19] <-NULL
row.names(distributiontable) <- return2$return2
write.xlsx(distributiontable, sfilename, row.names = TRUE, sheetName =
"Distribution_Table")

#Define discrepancies table tables
discrepanciestable <- return2
discrepanciestable[1:21] <-NULL
row.names(discrepanciestable) <- return2$return2
write.xlsx(discrepanciestable, sfilename, row.names = TRUE, sheetName =
"Discrepancies_Table")

#discrepanciestbl1
discrepanciestbl1 <- discrepanciestable[,1]
discrepanciestbl1 <- as.data.frame(discrepanciestbl1)
#View(discrepanciestbl1)
colnames(discrepanciestbl1)<-"Value"
discrepanciestbl1$date <- as.Date(return2$return2)
ggplot(discrepanciestbl1,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

#discrepanciestbl2
discrepanciestbl2 <- discrepanciestable[,2]
discrepanciestbl2 <- as.data.frame(discrepanciestbl2)
#View(discrepanciestbl2)

```

```

colnames(discrepanciestbl2)<-"Value"
discrepanciestbl2$date <- as.Date(return2$return2)
ggplot(discrepanciestbl2,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

#discrepanciestbl3
discrepanciestbl3 <- discrepanciestable[,3]
discrepanciestbl3 <- as.data.frame(discrepanciestbl3)
#View(discrepanciestbl3)
colnames(discrepanciestbl3)<-"Value"
discrepanciestbl3$date <- as.Date(return2$return2)
ggplot(discrepanciestbl3,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

#discrepanciestbl4
discrepanciestbl4 <- discrepanciestable[,4]
discrepanciestbl4 <- as.data.frame(discrepanciestbl4)
#View(discrepanciestbl4)
colnames(discrepanciestbl4)<-"Value"
discrepanciestbl4$date <- as.Date(return2$return2)
ggplot(discrepanciestbl4,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

#discrepanciestbl5
discrepanciestbl5 <- discrepanciestable[,5]
discrepanciestbl5 <- as.data.frame(discrepanciestbl5)
#View(discrepanciestbl5)
colnames(discrepanciestbl5)<-"Value"
discrepanciestbl5$date <- as.Date(return2$return2)
ggplot(discrepanciestbl5,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

#discrepanciestbl6
discrepanciestbl6 <- discrepanciestable[,6]
discrepanciestbl6 <- as.data.frame(discrepanciestbl6)
#View(discrepanciestbl6)
colnames(discrepanciestbl6)<-"Value"
discrepanciestbl6$date <- as.Date(return2$return2)
ggplot(discrepanciestbl6,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

#discrepanciestbl7
discrepanciestbl7 <- discrepanciestable[,7]
discrepanciestbl7 <- as.data.frame(discrepanciestbl7)
#View(discrepanciestbl7)
colnames(discrepanciestbl7)<-"Value"
discrepanciestbl7$date <- as.Date(return2$return2)
ggplot(discrepanciestbl7,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

```

```

#discrepanciestbl8
discrepanciestbl8 <- discrepanciestable[,8]
discrepanciestbl8 <- as.data.frame(discrepanciestbl8)
#View(discrepanciestbl8)
colnames(discrepanciestbl8)<-"Value"
discrepanciestbl8$date <- as.Date(return2$return2)
ggplot(discrepanciestbl8,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")

#discrepanciestbl9
discrepanciestbl9 <- discrepanciestable[,9]
discrepanciestbl9 <- as.data.frame(discrepanciestbl9)
#View(discrepanciestbl9)
colnames(discrepanciestbl9)<-"Value"
discrepanciestbl9$date <- as.Date(return2$return2)
ggplot(discrepanciestbl9,aes(x=date, y=Value)) +
  geom_line(color = "#FC4E07")
return1 <- benford(data$Cikis_Tutar, number.of.digits = 1)
return2 <- plot(return1)
#View(return2)

#Statistics
#return2 <- getBfd(return1)
#View(return2)

# Suspicious
return3 <- getSuspects(return1, data)
#View(return3)

return4 <- suspectsTable(return1)
View(return4)
#Create Report
write.xlsx(return3, sfilename, sheetName = "Suspicius_Records")

```

REFERENCES

- Alias, N. F., Nawawi, A., & Salin, A. S. A. P. (2019). Internal auditor's compliance to code of ethics. *Journal of Financial Crime*.
- Benford, F. (1938). The law of anomalous numbers. *Proceedings of the American philosophical society*, 551-572.
- Byrnes, P. E., Al-Awadhi, A., Gullvist, B., Brown-Liburd, H., Teeter, R., Warren Jr, J. D., & Vasarhelyi, M. (2018). Evolution of auditing: From the traditional approach to the future audit. *Continuous auditing: Theory and application*, 285-297.
- C.Cinelli (2018). Package 'benford.analysis' URL: <https://cran.r-project.org/web/packages/benford.analysis/benford.analysis.pdf>
- Chan, D. Y., & Vasarhelyi, M. A. (2011). Innovation and practice of continuous auditing. *International Journal of Accounting Information Systems*, 12(2), 152-160.
- Coderre, D., & Police, R. C. M. (2005). Global technology audit guide: continuous auditing implications for assurance, monitoring, and risk assessment. *The Institute of Internal Auditors*, 1-34.
- Durtschi, C., Hillison, W., & Pacini, C. (2004). The effective use of Benford's law to assist in detecting fraud in accounting data. *Journal of forensic accounting*, 5(1), 17-34.
- Fewster, R. M. (2009). A simple explanation of Benford's Law. *The American Statistician*, 63(1), 26-32.
- Gray, D. (2008). Forensic Accounting and Auditing: Compared and Contrasted to Traditional Accounting and Auditing. *American Journal of business education*, 1(2), 115-126.
- Groomer, S. M., & Murthy, U. S. (1989). Continuous auditing of database accounting systems using embedded audit modules. *Journal of Information Systems*, 3(1), 53-69.
- Ibrahim, M. A., Ali, E. I. E., Ismail, S. S. S., & Bidin, Z. (2020). Qualified audit reports of local authorities in the northern states of Malaysia. *Malaysian Management Journal*, 8(2), 77-86.
- IIA. (2004). *The Professional Practices Framework*.
- Kumar, K., & Bhattacharya, S. (2007). Detecting the dubious digits: Benford's law in forensic accounting. *Significance*, 4(2), 81-83.

- Lu, F., Boritz, J. E., & Covvey, D. (2006, June). Adaptive fraud detection using Benford's law. In Conference of the Canadian Society for Computational Studies of Intelligence (pp. 347-358). Springer, Berlin, Heidelberg.
- Moon, D., & Krahel, J. P. (2020). Continuous risk monitoring and assessment: New component of continuous assurance. *Journal of Emerging Technologies in Accounting*, 17(2), 173-200.
- No, W. G., & Vasarhelyi, M. A. (2017). Cybersecurity and continuous assurance. *Journal of Emerging Technologies in Accounting*, 14(1), 1-12.
- Paape, L. (2007). Corporate governance: The impact on the role, position, and scope of services of the internal audit function (No. 111).
- Pimbley, J. M. (2014). Benford's law and the risk of financial fraud. *Risk Professional*, 1-7.
- PricewaterhouseCoopers. (2020). Global Economic Crime and Fraud Survey 2020. PwC. Retrieved 6 April 2020, from <https://www.pwc.com/gx/en/services/advisory/forensics/economic-crime-survey.html>
- Sarens, G., & De Beelde, I. (2006). Building a research model for internal auditing: insights from literature and theory specification cases. *International Journal of Accounting, Auditing and Performance Evaluation*, 3(4), 452-470.
- Silva, W. B. D., Travassos, S. K. D. M., & Costa, J. I. D. F. (2017). Using the Newcomb-Benford Law as a Deviation Identification Method in Continuous Auditing Environments: A Proposal for Detecting Deviations over Time. *Revista Contabilidade & Finanças*, 28(73), 11-26.
- Singh, K., & Peter, B. (2020). Implementing Benford's law in continuous monitoring applications. *Accounting and Management Information Systems*, 19(2), 379-404.
- Spekle, R. F., Van Elten, H. J., & Kruis, A. M. (2007). Sourcing of internal auditing: An empirical study. *Management Accounting Research*, 18(1), 102-124.
- UTKU, M., & KAYA, Y. (2020). Islamic Finance Auditing Standards and Its Status Against International Standards on Auditing. *Management & Economics*, 373.
- Warren, D., & Smith, M. (2006). Continuous auditing: an effective tool for internal auditors. *Internal Auditing*, 21(2), 27-35.