Accounting manipulation -
analyzing corporate subsidy recipients during the covid-19 pandemic

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Abstract

In response to the reported increase in accounting crime and suspected fraud in conjunction with the adjustment subsidies initialized during the covid-19 pandemic of 2020, we conducted a study examining accounting manipulation. Based on an explanatory theory for fraud, the Fraud Triangle, we theorize that the financial circumstances that companies experienced during the pandemic and the governmental subsidies created an environment where accounting manipulation could occur. We obtained a unique set of unpublished data from the Swedish Tax Agency. Two common models for detecting accounting manipulation were then applied to a large sample of Swedish companies. We applied a version of the Jones Model to detect potential earnings management and Benford's Law to detect fraudulent manipulation of the firms' reported loss of revenue. Our results indicate earnings management and fraudulent reporting for some industries but no broad indication of systematic accounting manipulation across all industries. However, we suggest future research on this topic to further understand how accounting manipulation occurs in distressed industries.

Keywords: accounting manipulation; fraud; earnings management; Benford's Law; the Jones Model

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Contents

1 Introduction

Jones (2011) traces accounting manipulation to the beginning of modern-day bookkeeping and 15th-century mathematician Luca Pacioli. In more recent times, the outbreak of the covid-19 pandemic led to drastic changes within the field of accounting in Sweden. According to a report conducted by the Swedish Economic Crime Authority (Ekobrottsmyndigheten, 2020), the sudden increase in government subsidies and the addition of new laws regarding these subsidies has been identified as potential trigger for economic crime. This is supported by BRÅ (2022), who states that reported accounting crime has increased during the initial year of the pandemic.

In their 2020 Report to the Nations, ACFE (2020) studied over 2.500 cases of occupational fraud from all over the world. They claim that 14% of fraud was committed by the accounting department, and while financial statement fraud is the least common category of fraud occurring in 10% of cases it results in the highest median loss out of all types of occupational fraud. This is supported by Gee and Button's (2019) report, which estimates the global cost of financial fraud in 2019 at 3,89 trillion GBP (46,94 trillion SEK).

While fraudulent accounting is illegal, Perols and Lougee (2011) claim a connection between accounting fraud and the legal grey zone of earnings management. According to Perols and Lougee (2011), earnings management in prior years could indicate upcoming accounting fraud. Further, Plenborg and Kinserdal (2021) discuss specific situations where fraud could be more prevalent. They mention financial distress and changes in rules and regulations as two situations where fraud could be more common. Due to the ubiquity of these risk factors during the covid-19 pandemic, one might hypothesize that accounting fraud has increased during this period. However, there is currently no empirical evidence with which to evaluate that conjecture.

1.1 Aim and contribution

This study aimed to apply the Jones Model and Benford's Law to detect accounting manipulation on, to our knowledge, a previously unpublished dataset of companies that received subsidies during 2020 provided by the Swedish Tax Agency. Governmental subsidies in Sweden have yet to be researched to a significant extent, which is why this study examined whether there are indications of accounting manipulation in companies that received subsidies during the initial phases of the pandemic. There are also several academically relevant methodological contributions to be made using the Jones Model as well as Benford's Law. Alali and Romero (2013) state the need for research using Benford's Law on the industry level and with regard to the Jones Model, our study contributes to the existing literature by also including smaller private companies in our sample. Most previous research is primarily focused on publicly traded firms according to Svanström (2008). Further, previous research on accounting manipulation in companies in distress is inconclusive (Iatridis & Dimitras (2013). The main research question for this study is, therefore:

Are there any indications of accounting manipulation among companies that received subsidies during the initial year of the pandemic?

1.2 Findings and implications

To examine the prevalence of accounting manipulation during the pandemic, we utilized two common methods for identifying accounting manipulation. The Jones Model is used for detecting earnings management by measuring discretionary accruals (Jones, 1991). We also used Benford's Law, which examines the frequency of leading digits compared to expected proportions, to detect accounting fraud. If the dataset does not conform to the expected proportions, manipulation can be suspected. Benford's Law was previously applied by, among many others, Grammatikos and Papanikolaou (2020) and Alali and Romero (2013).

Our study identifies tendencies of increased earnings management in two of the twelve studied industries and potential fraudulent applications in five of twelve industries. The results are not convincingly supported by the Fraud Triangle, a theoretical descriptor of the behavioral precursors of fraud. In accordance with previous research, there are significant differences between industries. However, considering earnings management and accounting fraud as a common proxy for accounting manipulation, there are clear tendencies among certain industries that this is present during the covid-19 pandemic with regards to governmental subsidies.

2 Background

This section presents a short background to the covid-19 pandemic and its effect on Swedish society, as well as an overview of the newly implemented adjustment subsidies.

The covid-19 pandemic gave rise to several significant changes, both in Swedish society and in actions taken in its legislative body. A new law based on the adjustment subsidies (Law 2020:548) was enacted, which clarified which authority should be responsible, how the subsidies should be audited, and more. We highlight some of the critical milestones during the pandemic to bring attention to the changes that can affect the analysis of accounting information from these years.

- 2020-03-11 - WHO officially declared the disease as a pandemic.
- 2020-03-24 - Regulations regarding the number of guests at restaurants and bars were enacted.
- 2020-06-17 - Law (2020:548) on adjustment subsidies is enacted.
- 2020-07-01 - Regulations regarding sickness benefits for employees with covid-19 are enacted.
- 2020-09-01 - Last day for applications for adjustment subsidies for the period march & april 2020.
- 2020-10-19 - Stricter local recommendations regarding meeting other people than the household are sent out.
- 2020-11-30 - Last day for applications for adjustment subsidies for the period may, june & july 2020.
- 2020-12-27 - Vaccinations begin.
- 2021-04-30 - Last day for applications for adjustment subsidies for the periods august - december 2020.

In order for companies to receive the adjustment subsidies, they had to report at least a 30-50% loss of revenue to get 70-90% of their fixed costs covered by the subsidies (Regeringen, n.d). The fixed costs considered are, for example, insurance, electricity, interest, property tax, leasing, heating, and franchise costs (Skatteverket, n.d. A). In certain circumstances, subsidies can also be received for administrative costs. Another criterion for receiving the subsidy is that no dividends were paid out some months before and after the subsidy is received. The requirements were formulated to prevent recently started and inactive companies from applying for adjustment subsidies. During 2020, the adjustment subsidies were applied periodically, meaning several periods were available for application during the year. This means that one company could apply for adjustment subsidies several times during the year, once per period. The loss of revenue is calculated compared to the same period the prior year and is not dependent on the aggregate revenue for the entire fiscal year.

3 Theoretical and conceptual framework

In this section, we present a brief conceptual background on accounting manipulation and the Fraud Triangle.

3.1 Accounting manipulation

Accounting manipulation can be defined in a number of ways. In Sweden, accountants must work within the limits of good accounting practice. Good accounting practice lacks a clear set of rules but rather acts as a framework within which different companies can adapt their accounting to fit their business. Within the concept of accounting manipulation exists both the legal grey zone of earnings management and strictly illegal accounting fraud. Schuchter and Levi (2014) state that fraud is often defined as a breach of trust in a business environment, without the use of force, which brings an unfair economic advantage. Although there is not one definitive definition of earnings management, it can be described as when managers intentionally use their judgment in financial reporting and transactions to manipulate financial reports to mislead stakeholders about the underlying economic reality of the firm. This is also true when managers use discretion to alter financial information that would influence contractual outcomes that depend on reported accounting numbers, such as a debt covenant (Healy & Wahlen, 1999). According to this definition, companies who made a deliberate attempt to understate their earnings during the covid-19 pandemic in order to qualify for government subsidies would be considered to have performed earnings management, and possibly also fraud.

Earnings management can be divided into two main fields of research, accruals-based earnings management, and real earnings management. Accruals-based accounting has an advantage in terms of discretionary flexibility for example when it comes to large transactions that are completed over time to give a more accurate view of the transaction (Plenborg & Kinserdal, 2021). This flexibility however can be used by managers to exercise discretion by deferring costs or revenues from one period to another in order to mislead one or more stakeholders. Accounting information based on cash in- and outflows on the other hand enhances the users' ability to assess the future cash flows, liquidity, solvency, and financial flexibility of a firm (Plenborg & Kinserdal, 2021). On the contrary, accruals-based accounting information, such as the balance sheet can account for uncompleted transactions. This allows for flexibility in the valuation of assets over time since cash flow-based accounting fails to accurately measure the actual earnings capacity of investments, due to the varying nature of cash in- and outflows over time (Plenborg

& Kinserdal, 2021). Roychowdhury (2006) describes real earnings management as a departure from normal operational activities that are motivated by a manager's desire to mislead one or more stakeholders in the process. Examples of these types of operational activities could be example price discounts or a reduction in discretionary expenditure. Such deviations from normal operations can affect the financial reporting of a company without directly modifying accounting information. Perols and Lougee (2011) discuss accruals-based earnings management[1] and claim that firms can manage their earnings using discretionary accruals while still being entirely legal. However, they also claim that these accruals have to reverse over time, which means that these firms are left with two choices. They can either deal with this reversal of accruals or commit accounting fraud in order to offset the accruals (Perols & Lougee, 2011). Considering this need for offset, their study indicates a positive relationship between prior earnings management and fraud.

3.2 The Fraud Triangle

A model to understand the organizational environment is called the fraud triangle. The standard view is that this model includes the dimensions of pressure, opportunity, and rationalization, which can be described as why people in organizations might commit fraud (Albrecht & Wernz, 1993; Shuchter & Levi, 2014; Stuart, 2011). Stuart (2011) explains that there must exist pressure on management to commit fraud. According to Schuchter and Levi (2014), pressure often stems from performance-based pay, pressuring managers to show outstanding performance for their gain. Pressure can also stem from factors outside of the organization, such as the macro-economic situation, or from inside the organization such as colleagues or managers. Schuchter and Levi (2014) describe opportunity as the employee's estimation of how likely it is to succeed with the fraud. For example, the use of an auditor can often reduce accounting manipulation (Reguera-Alvarado, de Fuentes & Laffarga (2018), thus reducing the opportunity to commit fraud. Lastly, Schuchter and Levi (2014) claim that employees will often try to justify their decision to commit fraud. If they cannot rationalize their behavior to themselves, they will most likely not commit fraud. According to Schuchter and Levi (2014), fraud is considered highly unlikely if one of these three factors is missing. If all three factors are present, fraud is, on the other hand, considered highly likely.

Lokanan (2015) claims that using the fraud triangle might lead researchers to disregard other factors that might impact the occurrence of fraud. He also claims that the model assumes that

[1] Accruals-based earnings management is hereon referred to as "earnings management" unless otherwise specified.

fraud is the exception and that most cases do not lead to fraudulent activity. This is generally true (Albrecht & Wernz, 1993; Shuchter & Levi, 2014; Stuart, 2011). However, Lokanan (2015) claims that the Fraud Triangle does not consider people who actively try to commit fraud but rather those who get the opportunity to do so and did not intend to commit fraud from the start.

4 Literature Review

In this section, we present an overview of previous research regarding accounting manipulation. We then present a summary of the literature and in the last subsection, we present the working hypotheses of the study.

4.1 Previous research

Jones (1991) conducted a study of the amount of earnings management in US firms during import relief investigations periods and hypothesizes that when companies are presented with an outside factor, from which the company would benefit by understating certain accounting figures, it would in turn lead to an increase in earnings management. The study found that firms engaged in a larger amount of earnings management during relief investigations compared to the period in which there were no investigations. Similarly, Lim and Matolcsy (1999) also investigated governmental policies' effect on earnings management and showed that companies that were subject to price-control investigations by the Australian government in the 1970s exhibited higher levels of earnings management during the time of scrutiny compared to periods in which they were not being investigated. This conclusion lends support to the argument that external governmental factors that incentivize misleading stakeholders by financial figures have a clear connection to the amount of earnings management.

According to previous research on earnings management during times of financial crisis, there are many reasons why reported earnings may be adjusted upwards during financial distress. These reasons could, according to Filip and Raffournier (2014) be; making up for the loss in operational performance; trying to increase a falling stock price; or the presence of debt covenants. There also exist incentives to manage earnings downwards, especially for companies undergoing debt restructuring (Filip & Raffournier, 2014). They also found that earnings management significantly decreased during the financial crisis of -08 and point to the possibility that the cost of engaging in earnings management might have outweighed the potential benefit of earnings management. Kousundis et al. (2013) similarly concluded that the quality of the reporting improved during the financial crisis of -08. However, Kousundis et al. (2013) also found that as the earnings management incentives increase, the quality of the reported earnings decreases. Iatridis and Dimitras (2013) study have shown differences between countries during periods of the financial crisis in which some countries show either an increase or decrease in earnings management. Filip and Raffournier (2014) point out that most previous research on earnings management does not consider the macroeconomic environment in which the firm operates. Although the results from these studies are somewhat inconclusive as to how earnings management tends to change during times of financial crisis, an increase in incentives for earnings management decrease the quality of the reported accounting figures.

Alali and Romero (2013) have analyzed public U.S companies over a ten-year period and found that when regulated, the total amount of accounting manipulation decreased. A similar study was performed by Grammatikos & Papanikolaou (2020), in which they analyzed banks during a period of distress in the financial crisis in -08. They conclude that distressed banks have a higher tendency and incentive to perform accounting manipulation to conceal poor performance.

4.2 Literature synthesis

When changes in the legal framework happen as fast as they have done during the covid-19 pandemic, Plenborg and Kinserdal (2021) claim that fraudulent behavior could become more frequent. We recognize the importance of both earnings management and fraud within the realm of accounting manipulation. We specifically acknowledge the connection between the two factors as earnings management acts as a precursor for fraud, according to Perols and Lougee (2011). As a result of the covid-19 pandemic and its effect on companies, based on the assumed prevalence of all three factors in the Fraud Triangle, we believe accounting manipulation to be present. An opportunity occurs to receive subsidies and pressure to save one's company. Rationalization is a highly individual factor, but based on the increase in reported accounting crime and the prevalence of the self-serving bias, we assume this to be present as well.

Table 1: Summary literature

This table presents a summary of relevant literature regarding factors affecting accounting manipulation. Some literature also discussed the effect of financial distress on accounting manipulation, as summarized below.

	Accounting manipulation		
Author	Effect on earnings management (EM)	Effect on Fraud	Effect of financial distress
Jones (1991)	Governmental scrutiny increase EM.	-	-
Lim & Matolcsy (1999)	Governmental scrutiny increase EM.	-	-
Filip & Raffournier (2014)	Debt restructuring increase EM.	-	Distress decrease EM.
Kousundis et al. (2013)	-	-	Distress decrease EM.
Iatridis & Dimitras (2013)	Inconclusive.	-	Inconclusive.
Reguera-Alvarado, de Fuentes & Laffarga (2018)	External control reduce accounting manipulation.		-
Plenborg & Kinserdal (2021)	-	Fast legal changes increase fraud.	-
Alali & Romero (2013)	-	Regulation decrease fraud.	-
Grammatikos & Papanikolaou (2020)	-	-	Distress decrease fraud.

4.3 Hypotheses

To answer the overarching research question and identify potential indications of accounting manipulations during the initial year of the pandemic, we intend to apply each hypothesis to each industry individually, as suggested by Alali and Romero (2013). Hypothesis 1 stems from the assumption that the incentives to manage earnings increase when there is a possibility that it leads to a financial benefit, as claimed by Jones (1991) and Lim and Matolcsy (1999). However, if the companies are distressed both Filip and Raffournier (2014) and Kousundis et al. (2013) suggest that earnings management could decrease. Hypothesis 2 is based on the results by Grammatikos and Papanikolaou (2020), which leads us to believe that distressed companies are incentivized to manipulate their accounting. Moreover, both hypotheses are based on the assumption that the factors of the Fraud Triangle are prevalent.

H1: There is a statistically significant increase in earnings management in 2020 compared to 2019.

H2: The reported loss of revenue does not conform to the expected proportions of Benford's Law.

5 Method

This section introduces the steps taken to collect and handle the data, followed by a detailed explanation of the steps taken and considerations made to perform the analyses based on the two models. We then finish the section with a discussion on the reliability and validity of the study.

5.1 Data collection

We initially gathered, to our knowledge, previously unpublished data from the Swedish Tax Agency (STA). Our dataset contained information on all applications for adjustment subsidies in 2020. The dataset included information such as organization numbers, what industry the company operated in, acquired subsidies, and reported loss of revenue. The financial information provided is entered manually by the company itself in the application process, such as loss of revenue, fixed costs, and auditing costs. From this list of organizational numbers, we excluded companies who had their application for adjustment subsidy rejected. These exclusions were made because we noted some apparent user mistakes in the data. For example, one company reported a loss of revenue approximately 130 times their annual revenue, when for comparison, their actual loss of revenue from 2019 to 2020 only was about 45%. In order not to skew the results with invalid applications, we excluded the rejected applications from the sample. However, the STA did not provide any additional information as to why the application was rejected. The effect of the exclusions on sample size can be seen in Table 2 and 3. Excluding the applications that the STA rejected had several benefits. Firstly, we only study cases where companies actually have received subsidies, which increases the relevance in practice for this study. Secondly, we do note that the conformity to the expected distributions of Benford's Law would most likely differ if we chose to include all applications, but we deem this difference to be acceptable in light of the previously mentioned benefits. With this in mind, it is however possible that our results show higher conformity since we already have excluded potential fraudulent or erroneous entries due to the rejections by the STA.

Even if no explanation was provided for the rejections by the STA, they are actively working to reduce fraudulent reports by companies (Skatteverket, n.d. B). This is done both by receiving tips from whistleblowers or the public, but also by tax audits. Tax audits imply that the STA visits the company to audit their accounting and documentation. They also periodically select industries in aimed audits (Skatteverket, n.d. B). The STA does not specify any specific measures to prevent fraud in regards to the adjustment subsidies, other than their regular tax audits. Some, but not all, applications were audited before the application was sent into the STA, based on the size of the requested subsidy. All applications requesting more than 100 000 SEK had to be audited. While these audits might have decreased the incentive to enter fraudulent accounting information (Reguera-Alvarado, N., de Fuentes, P. & Laffarga, J., 2018), even the International Standards on Auditing (IAASB, 2021) claim that the reasonable assurance expected of an audit is not an absolute level of assurance. ISA 200 explicitly claims that there are inherent limitations in all audits and ISA 240 elaborates on this by claiming that the risk of not detecting intentional fraud is higher than that of detecting erroneous accounting (IAASB, 2021).

Based on the companies left in the dataset after excluding the rejects, we gathered information from their annual reports to use in conjunction with the Jones Model. This data was gathered from Retriever Business, which gets access to their data from the Swedish Companies Registration Office. We gathered data for the fiscal years ending in 2018, 2019, and 2020. 2018 and 2019 were included because the preceding year is necessary when applying the Jones Model. Even though companies could continue to apply for adjustment subsidies in 2021 and 2022, data from these years were not included because, as per the time of writing this thesis, most final accounts had not been closed yet.

5.1.1 Sample adjustment

We analyzed the same industries across both models. This resulted in the exclusion of seven industries, which resulted in 748 companies being excluded from the Jones Model. Additionally, we excluded companies with less than one employee to avoid dormant companies in our sample. Companies with less than 100 000 SEK in reported revenue for 2018, 2019, or 2020 were also excluded. The inclusion of dormant or not operating companies during at least one of our sample years would have prevented us from applying the Jones Model correctly, thus affecting our results. Furthermore, this adjustment was also made to avoid sampling companies that started their operations in 2019, thus worsening comparability between 2019 and 2020. The exclusions of inactive companies in the Jones Model resulted in 7 069 companies being excluded from the sample. The final sample used consisted of 16 740 companies, as shown in Table 2.

Table 2: Exclusion of samples for the Modified Jones Model

This table shows the number of excluded companies, as well as the accumulated sample size left to analyze and each reason for exclusion.

	# of companies excluded	**Acc. companies**
Initial data from STA		26 156
Rejected subsidy	1 599	24 557
Inactive companies	7 069	17 488
Excluded industries	748	16 740

When analyzing the applications using Benford's Law, we excluded companies that reported less than 100 SEK loss of revenue as per Nigrini's (2012) recommendation. Seven industries were excluded due to a lack of records, resulting in 4 649 applications being removed from the final sample. Table 3 shows that the final sample for Benford's Law was 50 665 applications.

Table 3: Exclusion of samples for Benford's Law

This table shows the number of excluded companies, as well as the accumulated sample size left to analyze and each reason for exclusion.

	# of companies excluded	**Acc. companies**
Initial data from STA		60 446
Rejected subsidy	5 048	55 398
Less than three digits	84	55 314
Excluded industries	4 649	50 665

We chose our dataset since the applications were suspected of manipulation (Ekobrottsmyndigheten, 2020). At the same time, it was easy for the companies to enter malicious information or round up, in which case Benford's Law would indicate wrongful entries. The fraudulent removal of, for example, sales entries in order to decrease revenue would according to Durtschi, Hillison, and Pacini (2004) result in non-conformity with the expected proportions of Benford's Law.

We used information from the companies' financial statements to analyze using the Jones Model and the reported loss of revenue from the applications to analyze using Benford's Law. These two different data types were used to study a more nuanced picture of accounting manipulation during the pandemic. The Jones Model has to be applied to financial statement information, which we gathered on a fiscal-year basis. We do note that the data collected for Benford's Law contains intra-fiscal year information, while the data collected for The Jones Model only contains information from the closing statements of the fiscal year. This might lead to discrepancies in the results, discussed later in section 6.3.3.

Each company could apply for adjustment subsidies for several different periods during 2020 (Skatteverket, n.d. A), meaning that some companies appeared several times in the dataset. Suppose company X applied for the subsidy for three different periods during 2020. In that case, they appeared three times in the dataset to which we applied Benford's Law but only once in the dataset to which we applied the Jones Model. This is the reason for the difference in sample size between the analyses using Benford's Law and the Jones Model since we only could include the information in the annual report when using the Jones Model. Despite these differences in sample size, the companies we analyzed are the same for both models.

5.2 The Jones Model

5.2.1 About the Jones Model

Jones (1991) developed a model to estimate if firms that would benefit from import reliefs managed their earnings when investigated by the US government. Jones found that the results from the model were consistent with the hypothesis that managers decrease income during periods of relief investigations, hence an increase in earnings management was identified. Similar to previous research within the field of earnings management at the time (Healy, 1985; DeAngelo,1986), Jones based her model on the partition of total accrual ($TACC$) into non-discretionary (NDA) and discretionary accruals (DA) as shown in equation (1).

$$TACC_t = NDA_t + DA_t \tag{1}$$

Jones (1991) describes the discretionary component of total accruals as the portion where managers have the ability to exercise judgment and consequently the ability to engage in earnings management. Jones tried to control for the impact of a change in economic circumstances on a company's non-discretionary accruals and thus ended up with the model for the non-discretionary accruals for a company at a given year, as shown in equation (2).

$$NDA_t = \beta_1 (\frac{1}{TotalAssets_{t-1}}) + \beta_2 \left(\frac{\Delta REV_t}{TotalAssets_{t-1}}\right) + \beta_3 \left(\frac{PPE_t}{TotalAssets_{t-1}}\right) \tag{2}$$

5.2.2 Calculating total accruals

Our application of the Jones Model consists of three main steps. We began by calculating the total accruals for each company during 2019 and 2020. There are numerous different methods when it comes to calculating total accruals for a given period and previous studies make different adjustments to the calculation based on the availability of data and fit to the case at hand (Jones, 1991, Dechow et al. 1995, etc). Jones (1991) calculates the total accruals using equation (3)[2].

$$TACC_t = [\Delta CurrentAssets_t - \Delta Cash_t] - [\Delta CurrentLiabilities_t] - Depreciation_t \tag{3}$$

where:

$\Delta =$ change between time t and $t-1$

Svanström (2008) argues that calculating total accruals should consider accounting figures where accruals are commonly used. This consideration is also made by Barth, Cram and Nelson (2001) who studied the predictive ability of disaggregate accruals, split into six major groups. These accruals are calculated as changes in, similar to our grouping in equation (4), accounts receivable, inventory, accounts payable, depreciation, amortization, and other accruals. In consideration of data availability, we equate the current assets minus cash, in equation (3), to the sum of accounts receivables and inventory. We also equate current liabilities to accounts payable, thus leaving us with equation (4) explaining the calculation of total accruals used in this study. Limitations of our modification of the calculation of the total accruals are discussed in section 5.4.

$$TACC_t = \Delta AccountsReceivables + \Delta Inventory - \Delta AccountsPayable - Depreciation_t \tag{4}$$

where:

$$\begin{aligned}
&TACC_t &&= \text{Total accruals at year } t\\
&\Delta AcccountsReceivables &&= AccountsReceivables_t - AccountsReceivables_{t-1}\\
&\Delta Inventory &&= Inventory_t - Inventory_{t-1}\\
&\Delta AccountsPayable &&= AccountsPayable_t - AccountsPayable_{t-1}
\end{aligned}$$

[2]where Δ is calculated as the difference between time t and time *t-1*.

5.2.3 Cross-sectional industry analysis

The second step was to divide the sample into their respective industries to get an estimation of the discretionary accruals for each sector individually. This study applied a cross-sectional analysis on an industry level which differs from the original version of the Jones Model (Jones, 1991), since Jones uses time series to estimate the discretionary accruals over time. There are several reasons why we chose to make this methodological adjustment. Numerous studies indicate that, since accruals usually differ between industries, separating them and applying the Jones Model to each industry individually provides a more accurate result than studies that base their model on a time series (Subramanyam, 1996; Stubben, 2010; Cohen and Zarowin, 2010). These differences in earnings management between industries is supported by more recent research by for example Datta et al. (2013) who finds that firms with inferior pricing power and industries that are more competitive engage in more earnings management which further lends support to our choice of method.

Furthermore, a cross-sectional analysis of individual industries has the advantage of not only being less time-consuming than a time series analysis but also allowing us to use a larger sample for our analysis. Subramanyam (1996) describes these advantages as a consequence of the fact that the time series analysis requires far more data points for each company and therefore leads to the exclusion of many companies that would likely fail to meet the requirements over time. In our study, this aspect was considered since it likely would have resulted in a significant exclusion of our sample.

5.2.4 Application of the Jones Model

The third step is to apply the Jones Model to each of the companies within each industry to calculate the discretionary accruals by using equation (5).

$$\frac{TACC_t}{TotalAssets_{t-1}} = \beta_1 \frac{1}{TotalAssets_{t-1}} + \beta_2 \frac{\Delta REV_t}{TotalAssets_{t-1}} + \beta_3 \frac{PPE_t}{TotalAssets_{t-1}} + \epsilon \quad (5)$$

where:

$TACC_t$ = Total accruals at year t

ΔREV $= Revenue_t - Revenue_{t-1}$

$\beta_1, \beta_2, \beta_3$ = *Industry specific parameters*

ϵ = *Residual*

Regressions were made using IBM SPSS for 2019 and 2020 in each industry. When applying the Jones Model, the residuals generated by the regression are interpreted as the discretionary accruals (Jones, 1991) and are the values on which the t-tests were based. The absolute value was used when calculating the mean of the residuals for 2019 and 2020 in each industry. T-tests were then used in order to determine if there was a significant difference in the mean value of the residuals when comparing 2019 to 2020 between the industries. The use of the absolute value of the residuals when performing the t-tests is in accordance with previous research on the topic (Frankel et al. 2002; Ferguson et al. 2004; Reynolds et al. 2004).

5.2.5 Critique of the Jones Model

Dechow, Sloan, and Sweeney (1995) direct criticism toward the ability of the Jones Model to measure earnings management since it is implicit in the model that revenue is non-discretionary. The original Jones Model was misspecified when applied to samples of firms with extreme financial performance by falsely rejecting the null hypothesis that there is no increase in earnings management (Dechow, Sloan, and Sweeney, 1995). The exclusion of non-discretionary accruals, which are affected by financial performance, can be mistaken for discretionary accruals, giving incorrect residuals. Another inherent problem with the original Jones Model is that other factors correlated with financial performance could increase the amount of managed earnings. This would result in the model correctly indicating an increase in earnings management, but the causes would be unknown. To account for this limitation, Dechow, Sloan, and Sweeney (1995) proposed a modified version where the changes in revenues are adjusted for the changes in receivables to account for the discretionary accruals in revenues. In this study, we lacked the necessary accounting information to make adjustments for net receivables, which was why the modified version was not applied.

Kothari et al. (2005) suggests that the Jones Model is misrepresentative when the sample is not randomly selected and that scientists instead look at a sample of firms that have undergone a specific change such as changing auditor. Kothari et al. (2005) argues that this misrepresentation primarily stems from the fact that such a change may lead to a more extreme result which in turn could affect the model negatively.

Despite this critique, there are no alternative measures as frequently used as the Jones Model. Measuring discretionary accruals using some form of the Jones Model is widely regarded as a well-established way to measure earnings management and earnings quality and has been demonstrated to be effective in numerous studies since its inception (Frankel et al., 2002; Larcker & Richardson, 2004; Antle et al., 2006).

5.3 Benford's Law

5.3.1 About the Law

Nigrini (2012) explains that Benford's Law indicates the frequency of leading numbers in sets of digits. The first, second, and first-two digits frequency should follow the distribution shown in Benford's Law. Should the sample distribution be significantly different from the expected distribution according to Benford's Law, this can cause concern as to whether the accounting data has been manipulated (Goh, 2019). Nigrini (2020) explains that Benford's Law applies to geometric or logarithmic sequences, i.e., sequences where the next term is the previous term multiplied by a common ratio. To exemplify, when receiving interest payments, the amount received increases based on the amount received previously and quickly snowballs into larger and larger amounts in real numbers, even if the percentage stays the same. This effect is also known as anatocism or the effect of compound interest.

On the other hand, Nigrini (2020) explains that Benford's Law does not apply to non-logarithmic/-geometric sequences, such as people's height or prices in a store. The expected frequencies for the initial and second digits according to Benford's Law are shown in Figure 1.

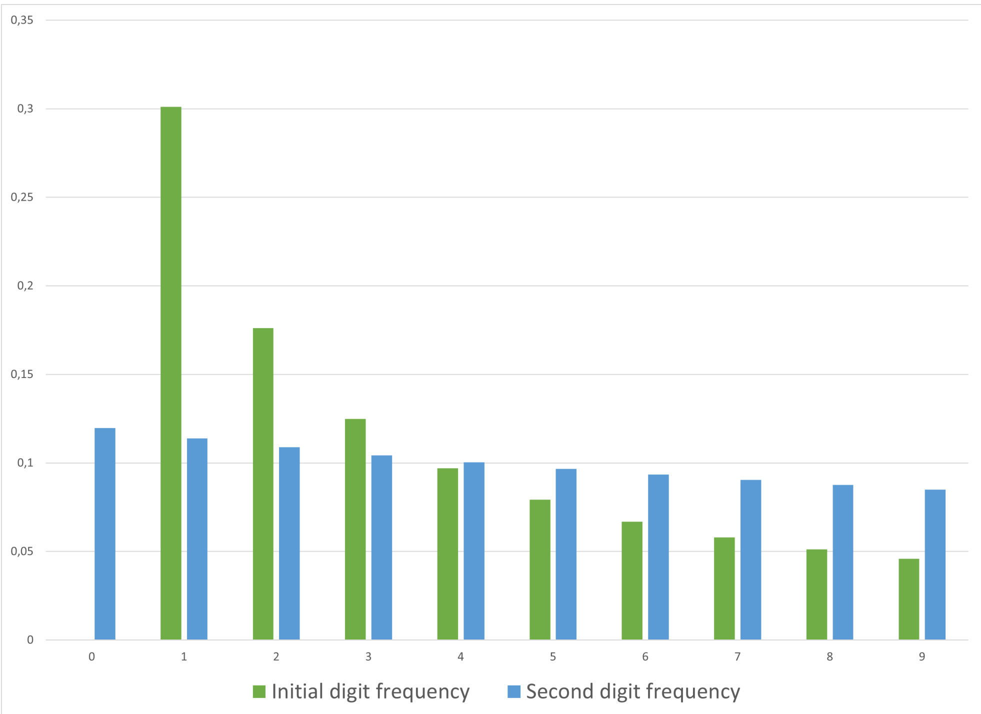

Figure 1: Expected frequencies according to Benford's Law

This figure shows the expected frequency calculated using Benford's Law. The frequency is shown on the Y-axis and the digit on the X-axis.

5.3.2 Prerequisites

Nigrini (2020) explains some of the criteria necessary to apply Benford's Law. For the most part, the dataset used should consist of at least four digits, although three-digit numbers are acceptable. Nigrini also claims that the dataset should consist of at least 1000 records since analyzing smaller datasets could create situations where the deviation from the expected frequency is unnaturally large.

Nigrini (2012) mentions other criteria for applying Benford's Law, which is the order of the mantissas. A mantissa[3] is the decimals of the logarithm of a number. If we, for example, have the number 24, the logarithm of that number is 1,38, where the mantissa of 24 is 38. To establish conformity to Benford's Law, the distribution of the mantissas has to align to a set of properties. Mathematically, the basis for Benford's Law is that the mantissas of the logarithms of the numbers in the records are evenly distributed over the dataset (Nigrini, 2012). Nigrini (2012) suggests a visual test of the mantissas. By sorting and plotting the mantissas in a histogram, conformity can be checked against a straight line. Moderately close conformity to the ideal mantissa requires using Benford's Law to analyze a dataset (Nigrini, 2012). Mantissa conformity was studied and referenced in Appendix 2.

Some other criteria Nigrini (2020) mentions are the fact that the dataset should contain more small values than large ones, i.e., have a positive skew, and that the values should not be identifiers for other items such as invoice numbers. Due to the mathematical basis of Benford's Law, it is commonly assumed that the result of mathematical calculations generally ought to conform to the expected distributions. Nigrini (2020) claims that accounting data generally conforms to these criteria and is a good fit to apply Benford's Law. This assumption is further supported by Durtschi, Hillison, and Pacini (2004), who support their claim by stating that revenue most often is the sum of multiplying price and quantity. Benford's Law has also been applied in many other situations, such as math (Hill, 1995) and crime statistics (Hickman & Rice, 2010). Grammatikos and Papanikolaou (2020) mention that Benford's Law, in contrast to other common economic models, does not rely on firm-specific variables but instead on the distributional properties of the underlying accounting information.

5.3.3 Digit tests

Benford's Law consists of three tests; primary, advanced, and associated (Nigrini, 2012). Depending on the task, the primary tests might satisfy the assignment, while others might need

[3] Stated more formally, the mantissa=log10(x)-int(log10(x)).

advanced and associated tests. In this study, we deem the primary tests to be sufficient, similarly to the method applied by Alali and Romero (2013). The primary tests are the first digit test, second digit test, and first-two digits tests. We apply the tests to the reported loss of revenue from the dataset.

According to Nigrini (2012), the first and second-digit tests are high-level tests that can be used as an initial guideline to identify which datasets incur the highest risk of fraud. The first and second digit tests also act as tests of reasonableness to see whether there is any form of conformity to the estimated proportions of Benford's Law. Should these two tests indicate nonconformity, one must question whether Benford's Law applies to the dataset. For example, in some instances, prices have abnormally high amounts of 0s and 9s, which is not necessarily a cause for concern. If the first digits do not conform to the expected proportion, one can still allow for conforming second and first-two digits without questioning the overall applicability to Benford's Law.

The first-two digits test shows greater detail than the first and second digits tests in that it indicates abnormal duplications in the data (Nigrini, 2012). The first-two digits test could identify psychological cutoff points, erroneous reimbursements, or similar patterns. In order to measure conformity to Benford's Law, Nigrini (2012) describes how the expected proportions are calculated as shown below:

$$Prob(D_1 = d_1) = log_{10}(1 + \frac{1}{d_1}) \tag{6}$$

$$Prob(D_2 = d_2) = \sum_{d_1=1}^{9} log_{10}(1 + (10d_1 + d_2)^{-1}) \tag{7}$$

$$Prob(D_1D_2 = d_1d_2) = log(1 + \frac{1}{d_1d_2}) \tag{8}$$

where:

$d_1 \quad = \{1,2,...,9\}$

$d_2 \quad = \{0,1,...,9\}$

$d_1d_2 = \{10,11,...,99\}$

Equation (6) represents the probability of the first digit, and (7) represents the probability for the second digit, as shown above. d_1 in equation (7) represents the first digit in the number. The expected proportions are later used in the conformity tests. Equation (8) represents the probability for the first two digits. While we only analyzed the reported loss of revenue using the primary digit tests, the inclusion of reported fixed costs would have resulted in more data points on which to base our analysis. To stay within reasonable scope for this thesis, we decided to focus on the reported loss of revenue, since this was the primary determining factor for who received the subsidies or not.

5.3.4 Conformity tests

There are several ways to assess conformity to Benford's Law. The four most common ways are the Z-statistic, Chi-Square, Kolmogorov-Smirnoff, and the Mean Absolute Deviation (MAD) test. However, Nigrini (2020) explains that both the Z-statistic, Chi-Square statistic, and the Kolmogorov-Smirnoff (K-S) statistic suffer from the excess power problem means that with large datasets, even minor deviations would result in non-conformity. Out of these methods, the MAD test ignores the number of records that made it appropriate to use when analyzing large datasets (Nigrini, 2012). Similar to Alali and Romero (2013), we used the MAD test in our study to assess conformity to Benford's Law. Based on the expected proportions shown in the equation above, we could compare them to the actual proportions using the Mean Absolute Deviation (MAD), which is calculated as shown in Equation (9).

$$MeanAbsoluteDeviation = \frac{\sum_{i=1}^{K} |AP - EP|}{K} \tag{9}$$

where:

AP = Actual proportion
EP = Expected proportion
K = Bins

The difference between AP and EP was calculated in absolutes. MAD was applied to all three primary tests, although the first-two digits test was the one in focus in this study, following recommendations by Nigrini (2012). As mentioned before, this focus was because the first-two digits test often is used to identify psychological cut-off points and rounding. Due to the nature of the dataset that we applied Benford's Law to, self-reported loss of revenue, we found this to be appropriate. Our assumption stemmed from the self-reporting aspect of the applications, as the managers in the companies handling the application for the subsidy could manually manipulate or erroneously round their estimated loss of revenue to receive more subsidy. As the prerequisites for receiving the adjustment subsidies stand, the loss of revenue had to be at least 30%. This could mean that there was pressure to round up the reported loss of revenue, which would be identified in the first two digits test.

When analyzing the MAD tests where the conformity results for the initial, second, and first-two digits tests differ, judgment is needed (Nigrini, 2012). This stems from the somewhat arbitrary nature of what values should be considered the critical cut-off points. For example, Aggarwal and Dharni (2020) claim that there are no such values. Alali and Romero (2013) support this view, claiming that there are no statistically proven cut-off values. Nigrini's (2012) values stem from his extensive testing of 25 different datasets, and the widespread use of these values is why we chose to apply them in our study. There is a possibility that the conformity of the first, second, and first-two tests differ, in which case Nigrini (2012) recommends a conservative approach to interpreting the conformity. We used the cut-off values given by Nigrini (2012) for these three tests, as shown in Table 4.

Table 4: Critical Values and conclusions for Various MAD Values

This table shows the acceptable MAD-values when calculated using the actual frequencies and the expected ones according to Benford's Law.

Digits	**Range**	**Conclusion**
First Digits	0,000 to 0,006	Close conformity
	0,006 to 0,012	Acceptable conformity
	0,012 to 0,015	Marginally acceptable conformity
	Above 0,015	Nonconformity
Second Digits	0,000 to 0,008	Close conformity
	0,008 to 0,010	Acceptable conformity
	0,010 to 0,012	Marginally acceptable conformity
	Above 0,012	Nonconformity
First-two Digits	0,0000 to 0,0012	Close conformity
	0,0012 to 0,0018	Acceptable conformity
	0,0018 to 0,0022	Marginally acceptable conformity
	Above 0,0022	Nonconformity

5.4 Reliability and validity

Reliability refers to the consistency of the measurement instruments over time. A highly reliable study would have yielded more similar results if the same study had been replicated. A study with low reliability would not be able to replicate the results if the same study was conducted at a different point in time (Bryman & Bell, 2011). We received raw data for the companies that received the adjustment subsidies, which we deem reasonably reliable. Furthermore, the financial figures used in the Jones Model were gathered from Retriever Business, which means there is a low risk of human error in the data gathering process. In addition to that, we clearly stated which companies had been excluded from the sample, which adds to the ability to replicate the study. With these factors considered, we deem that this study had high reliability.

Validity refers to the ability of the study to measure what it intends to measure (Bryman and Bell, 2011). Both the Jones Model and Benford's Law have commonly used methods of analyzing accounting manipulation (Alali & Romero, 2013, Dechow, Sloan & Sweeny, 1995, Grammatikos & Papanikolaou, 2020, Jones, 1991, Frankel et al., 2002).

Our choice to include other variables in our total accruals calculation, as compared to Jones (1991), might affect the validity of our study. The alteration to the included variables stems from data availability and could potentially lead to some earnings management being excluded from our analysis, leading to the study potentially not recognizing all discretionary accruals over the period. Nevertheless, many previous studies use different methods of measuring total accruals based on the data available (Jones, 1991; Frankel et al., 2002; Larcker & Richardson, 2004). In this study, our calculation includes a sufficient number of variables commonly subject to accruals, but including more variables might have improved the study's validity.

As mentioned previously, Dechow, Sloan, and Sweeney (1995) propose a modified version of the Jones Model. They address the implicit assumption of the original model that revenues are non-discretionary by including net receivables in their modified version. The accounting figures to calculate net receivables are also unavailable for this study, leading us to use the original version of the Jones Model. From a validity standpoint, this poses a potential problem because we assume that companies managed their revenues to a more significant degree in order to qualify for the subsidies. However, for this study, it is assumed that the earnings management captured from the original Jones Model will indicate the total amount of earnings management. Still, this study's validity could have benefited from using the modified version of the Jones Model proposed by Dechow, Sloan, and Sweeney (1995).

Our choice to apply the Jones Model to samples divided into industries increases the validity of the study. This stems from Subramanyam (1996), who claims that the amount of discretionary accruals usually differs between industries, as to why performing t-tests on the entire population could negatively affect the model's ability to predict earnings management.

6 Empirical analysis

This section presents the results from the Jones Model and the Benford's Law MAD tests. In the later part of this section, the results will be discussed.

6.1 The Jones Model

Descriptive statistics from the Jones Model analysis are presented in Appendix 4. In table 5, the t-test shows if there was a statistically significant difference between the mean values of the residuals from 2019 and 2020. "Construction", "Health and social care" and "Law and business" were all showing a significant difference in the mean value of the residuals. For the industry "Construction", the mean residual value was significantly lower than in 2020, while the industries of "Health and social care" and "Law and business" both showed significantly higher mean residual values in 2020 compared to 2019. This effectively indicates that the "Construction" industry decreased the amount of earnings management performed during 2020, while the other two industries, "Health and social care" and "Law and business" increased the number of earnings managed as compared to the previous year.

Table 5: T-test statistics per industry

This table presents the results of the t-tests and their respective critical cutoffs. ΔResidual is calculated between the years of 2019 and 2020 in accordance with the Jones Model.

Industry	**T-stat**	**Critical T-cutoff**	**ΔResidual**
Other service activity	-1,38	1,96	0,013
Construction	1,97**	1,96	-0,020
Property	0,16	1,97	-0,003
Motor vehicles	0,54	1,96	-0,003
Hotels and restaurants	-1,49	1,96	0,006
Information and communication	1,58	1,96	-0,027
Culture and leisure	-0,57	1,96	0,005
Production	0,71	1,96	-0,004
Transport and storage	1,11	1,96	-0,007
Rental, property service and travel	-0,45	1,96	0,017
Health and social care	-5,09***	1,96	0,058
Law and business	-3,21***	1,96	0,026

* indicates significance on the 10% level (2-tailed).

** indicates significance on the 5% level (2-tailed).

*** indicates significance on the 1% level (2-tailed).

6.2 Benford's Law

6.2.1 Prerequisite tests

We tested the dataset against all of the prerequisites mentioned in section 5.3.2. The mantissas were visually analyzed and deemed to conform to the criteria mentioned by Nigrini (2012). According to Nigrini (2012), the ideal properties of the mantissa are; an average of 0.5, the variance of 1/12, skewness of 0, and kurtosis of (-)6/5. Mantissa conformity is shown in Appendix 2.

6.2.2 Primary tests

We performed the primary tests based on industry. When analyzing this data using Benford's Law, we exclusively used the reported loss of revenue since this is the primary determining factor for receiving the subsidy (Regeringen, n.d.).

Table 6: Calculated MAD values per industry

This table shows the MAD-values calculated for each industry, for each of the three primary digit tests. It also shows which industries were removed due to a lack of sufficient sample size. Nigrini (2012) suggests nonconformity cutoffs for the first digit MAD at 0,015, second digit MAD at 0,012 and first-two digits MAD at 0,0022.

Industry	**First digit MAD**	**Second digit MAD**	**First-two digits MAD**
Other service activity	0,0078	0,0044	0,00182
Construction	0,0060	0,0048	0,00191
Property	0,0075	0,0089	0,00278
Finance and insurance		Too small sample	
Electricity, gas and heat suppliers		Too small sample	
Motor vehicles	0,0021	0,0040	0,00092
Hotels and restaurants	0,0019	0,0027	0,00068
Information and communication	0,0033	0,0058	0,00226
Agriculture and fishing		Too small sample	
Culture and leisure	0,0042	0,0042	0,00421
Public management and defence industries		Too small sample	
Production	0,0057	0,0051	0,00147
Transport and storage	0,0053	0,0026	0,00264
Education		Too small sample	
Rental, property service and travel	0,0030	0,0035	0,00107
Mining		Too small sample	
Health and social care	0,0112	0,0066	0,00257
Water supply and waste management		Too small sample	
Law and business	0,0058	0,0034	0,00114

When analyzing the MAD tests, the initial and second digit tests were indicative of whether there are any apparent deviations from the expected proportions. Neither industry indicated nonconformity for the first and second digits MAD tests. The first-two digits test is according to Nigrini (2012) the most reliable one for deciding conformity, which was why we focused our analysis on these results. Based on the results from the first-two digits test, "Property", "Information and communication", "Culture and leisure", "Transport and storage" as well as "Health and social care" indicated nonconformity.

6.3 Discussion

6.3.1 The Jones Model

When we analyzed the results of the Jones Model, we found that "Health and social care" and "Law and business" were the only industries where there was any indication that earnings management had increased during the pandemic. In contrast, most industries did not indicate any statistically significant change. We, therefore, rejected the null hypothesis for H1 for these two industries.

H1: There is a statistically significant increase in earnings management in 2020 compared to 2019.

In the case of "Construction", we could even observe a statistically significant decrease in the amount of earnings management. Overall our results were not generalizeable for the studied population as a whole, regarding the amount of earnings management during the pandemic.

As mentioned in section 5.2.5, Dechow, Sloan, and Sweeney (1995) argue that the original Jones Model might falsely reject the null hypothesis in companies with extreme financial performance. This is because extreme financial performance might lead to an increase in non-discretionary accruals, which the Jones Model incorrectly identifies as an increase in discretionary accruals. Most of the companies in our sample experienced extreme financial performance negatively, which is the entire basis for the subsidies. Our results seem to contradict the findings of Dechow, Sloan, and Sweeney (1995) since we did not reject the null hypothesis for the majority of our sample even though the conditions for extreme financial performance were supposedly met. This could suggest that the extreme financial performance that companies experienced during the pandemic is not linked to an increase in non-discretionary accruals excluded from the Jones Model. Our results also put into question what ought to be defined as extreme financial performance.

Our study differs from previous studies (Filip & Raffournier, 2014; Kousundis et al., 2013) on earnings management during the financial crisis of -08 because companies during the global pandemic were affected by governmental restrictions, contrary to the previous financial crisis which was instigated primarily by the actions of a specific sector. Filip and Raffournier (2014) mention several incentives to engage in earnings management during times of a financial crisis. We recognize several of these incentives during the pandemic, but we find no overwhelming statistically significant indication that this would be the case in our study. Our findings do not support the results of Filip and Raffournier (2014) or Kousundis et al. (2013) since we cannot identify any notable, industry-overarching, increase or decrease in earnings management for our sample overall.

Both Filip Raffournier (2014) and Jones (1991) talk about how although incentives for earnings management might be present, not all companies may be incentivized enough to engage in earnings management due to financial aspects that are inherent to each company. To exemplify this with a hypothetical scenario, a company that reports a loss of revenue that is not quite large enough to qualify for the subsidies, might have a larger incentive to engage in earnings management than the incentive for a company that already qualifies for the subsidies. This relative perceived benefit between individual companies could be a reason why we cannot see any indication that there was a significant increase in earnings management across all industries during the pandemic.

Some studies have also shown that managers are more willing to engage in real earnings management than accruals based earnings management (Bruns & Merchant, 1990; Graham et al., 2005). One reason as to why this is the case is argued by Dechow, Sloan, and Sweeney (1996) to be a result of accruals-based earnings management drawing more scrutiny and attention from regulators and auditors. This could be a possible explanation as to why the measured change in earnings management by using accruals is relatively low for our sample.

6.3.2 Benford's Law

To answer the second hypothesis, we used the results from the MAD-tests. The MAD-tests are not constructed in a way that generates a p-value, meaning we use Nigrini's (2012) cutoff values to reject the null hypothesis.

H2: The reported loss of revenue does not conform to the expected proportions of Benford's Law.

Based on the MAD-values in Table 6, we reject the null hypothesis for the industries "Property", "Information and communication", "Culture and leisure", "Transport and storage", and "Health and social care".

The results from Benford's Law were indicative of slight deviations from the expected proportions in specific industries. However, these results were not conclusive for the studied population as a whole, partly due to the uncertain nature of the MAD cutoff values established by Nigrini (2012). As mentioned earlier, we used Nigrini's (2012) critical cutoffs to determine nonconformity. Still, we could see quite large deviations within the more-or-less conforming industries, such as "Hotels and restaurants" with a MAD of 0.00068 while "Construction" still conforms with its MAD of 0.00191. Even if the industries did not indicate nonconformity, a lesser degree of conformity might be of more interest than samples with high degrees of conformity. We, therefore, encourage auditors and the Swedish Tax Agency, in particular, to utilize these results to conclude whether specific industries were more fraudulent in their applications than others, as this is a professional endeavor outside the scope of this study. As Nigrini (2017) states, Benford's Law could be used to determine audit samples, although his application is used explicitly for auditing individual companies. The application is in our study slightly different as we identify entire industries that might be of specific interest. However, we concluded our use of Benford's Law to be within the model's scope as suggested by Alali and Romero (2013).

Regarding the use of Benford's Law, Alali and Romero (2013) raise the issue of false positives, i.e., Type I errors concluding fraud where there is no fraud committed. They state that there may be some cases where there are reasonable business explanations for an overabundance of the first two leading digits. Our study lacked the data to conclude such business explanations as it requires analysis of individual companies, which was outside the scope of this thesis.

6.3.3 Overarching discussion

In the study by Perols and Lougee's (2011), it was clear cut as to whether the studied firms performed fraud or not. In the case of our study, we lacked the option to confirm the potential fraud indicated by our results. Perols and Lougee (2011) further claim that the fraudulent activities of firms often stem from a lack of options as a result of prior year income-increasing earnings management. This was an essential difference between this study and Perols and Lougee (2011) since the potential fraudsters in the case of this study have an incentive to "manage down" and lower revenue to increase earnings, contrary to most earnings management where the incentive lies in increasing reported revenue. Theoretically, higher MAD indicates more deviation from the expected Benford's Law proportions while higher absolute residual means indicate more discretionary accruals, i.e., earnings management.

Furthermore, Perols and Lougee (2011) suggest that the link between earnings management and fraud could be because earnings management in prior years leads to an increased probability of committing fraud due to earnings management. Our study differs since we did not infer that fraud is the result of earnings management but rather that earnings management and fraudulently reported numbers complement each other in these unique circumstances present during the pandemic. This could be an additional possible explanation for why our results differed from those concluded by Perols and Lougee (2011). Also, Grammatikos and Papanikolaou (2020) point to the difference between Benford's Law and the Jones Model. They highlight that Benford's Law does not rely on model estimations meaning that omitted variables or changes in underlying model parameters can cause deviation. Due to the simple nature of Benford's Law, when comparing to a regression-based model like the Jones Model, there might be too many unknown variables at play, making the results hard to compare. Alali and Romero (2013) support this, claiming that firm characteristics do not drive raw data analysis like Benford's Law. This means that accruals, which are inherently firm-dependent, are not directly comparable. They enforce their reasoning by claiming that it is possible to find results contrary to prior studies (Alali & Romero, 2013), which is in line with our findings. Additionally, the Jones Model studied the final accounts of the fiscal year due to availability. This, in contrast to Benford's Law which was applied to intra-year data, could lead to issues regarding intra-year adjustment of earnings management offsets. There is a possibility that this affects the possibility of capturing potential earnings management. As mentioned earlier, when companies apply for subsidies they do so for a specific period that is shorter than one year. In theory, this could mean that some companies could manage their revenue through accruals during the period in which they are applying for subsidies, only to reverse those accruals in a later period during the same fiscal year, in which they are not applying for subsidies and thus not being visible in the annual report. This should be considered when conducting a similar study.

Theoretically, the Fraud Triangle (Cressey, 1953) consists of opportunity, rationalization, and pressure. During the pandemic, we assumed the existence of all three factors. However, we recognized that they were not prevalent in all individual companies studied, as made apparent by our empirical results. Based on the industry mean operating margins[4] presented in Appendix 3, we believe that not all industries perceived enough pressure to perform accounting manipulation. While operating margin should not be compared across industries, since fixed costs determine how much adjustment subsidy is received, a low operating margin should theoretically increase the pressure to commit accounting manipulation (Shuchter & Levi, 2014). However, our results were inconclusive which could partially be because rationalization is a highly individual trait in the Fraud Triangle.

Another factor that, according to Plenborg and Kinserdal (2021), could increase the pressure to commit accounting manipulation is fast changes in the legal framework. As presented in section 2, the new law on adjustment subsidies was introduced quickly. However, the law was introduced simultaneously for all industries, thus should not skew the results towards either industry. We

[4]Operating margin=EBIT / revenue.

could also not control for this effect in our testing, however, this might be one such external factor for fraud which Lokanan (2015) suggests might be a reason for fraud not explicitly covered by the fraud triangle. Lokanan claims that the Fraud Triangle does not explicitly consider people actively trying to commit fraud. We recognize that our study disregarded individual psychological behavior which could affect the explanatory power of the theory.

7 Conclusions

This section begins with concluding remarks on the study performed, and finishes with a discussion on limitations and our suggestions for future research on the subject of accounting manipulation.

The occurrence of accounting fraud undermines the aim of accounting itself, to provide a truthful picture of the state of a company. The increase in reported accounting crime during the covid-19 pandemic is problematic at best, which is part of the reason why we chose to study the companies that applied for adjustment subsidies during 2020. As new laws were implemented quickly and many companies' revenue decreased drastically over a short period, we identified pressure to commit accounting manipulation amongst the most affected companies. Because of this, we gathered data on these specific companies and studied them based on two perspectives of accounting manipulation, earnings management, and fraud.

Our results show tendencies of earnings management and fraud in specific industries. However, not all companies on an aggregated level across all industries indicated accounting manipulation. However, we do not believe this specific result to be generalizable. Generally, companies performed well, and the overall risk for accounting manipulation was deemed relatively low on a macro-scale. We contributed to the existing theory on both the Jones Model as well as Benford's Law by mainly analyzing private firms. This study further contributes to accounting research by testing the effectiveness of these models on smaller companies. This could be of use since the accounting framework applied to these companies is generally more straightforward than, for example, IFRS.

7.1 Limitations and future research

There could be an issue regarding the timing of the end of the fiscal year and the finalization of accounts for certain companies affected by the regulations enacted in march 2020. If companies were financially affected by the regulations and closed their books in May, if they finalized their annual report before June when the new law was enacted, they might miss out on the chance to include the subsidies in their accounts for the fiscal year ending in 2020. However, we did not deem this to affect the study since, according to the Swedish law of Limited companies (2005:551 10§), companies must hold their annual general meeting within six months of the end of the fiscal year. This means that a company can change the accounting information during this period before the annual report has to be turned in and registered. The time passed between the initial regulations limiting the activity in March and the new law's enactment regarding the adjustment subsidies was shorter than six months. This means that no matter when the companies closed their books, they all had ample time to get information on the coming subsidies and make potential manipulations to their books before finalizing. However, the data from Retriever Business included all companies that applied for subsidies, no matter which fiscal year they used. This means that our data included all companies that closed their books during 2020, even if they closed their books before the new law of adjustment subsidy was enacted. We did not consider this an issue since the initial sample from the STA only included companies that applied for adjustment subsidies.

As mentioned previously, measuring earnings management with the Jones Model requires the separation of discretionary accruals from total accruals. Since some variables in the calculation of total accruals were excluded due to a lack of accessibility it is possible that our study did not identify some of the managed earnings in the excluded variables and should be mentioned as a limitation for the study.

We suggest future studies on the Jones Model to analyze the concept of extreme financial performance. As of writing this thesis, we have not found a specific interval for when this begins to affect the results. Since we did not perform a longitudinal study of earnings management, we cannot conclude prior-year earnings management. This could also be of interest for future studies, which could analyze earnings management for a longer duration in non-crisis times to control for that variable. We also suggest future studies on how Benford's Law can be best complemented by qualitative analysis, for example by interviewing relevant staff and analyzing individual accounts. This would allow for a more nuanced explanation to be reached, which would be a sensible complement to Benford's Law in order to explain certain nonconforming leading digits.

8 Appendices

8.1 Appendix 1. Prerequisite statistics for Benford's Law

This table shows the amount of companies in each industry for the analysis of Benford's Law. It also displays the lowest, highest, mean and median reported revenue numbers.

Table 7: Prerequisite statistics for Benford's Law industries.

Industry	**# of companies**	**Low**	**High**	**Mean**	**Median**
Other service activity	1 941	5 633	63 564 276	411 577	151 299
Construction	1 633	110	98 961 000	1 345 546	440 359
Property	1 176	8 028	51 225 910	987 514	350 642
Motor vehicles	7 541	116	542 703 485	3 129 734	453 402
Hotels and restaurants	15 552	372	870 968 457	1 994 706	611 056
Information and communication	1 380	6 329	340 482 605	2 131 613	273 613
Culture and leisure	3 064	100	614 647 958	2 550 523	286 373
Production	2 848	423	997 586 000	4 557 935	668 137
Transport and storage	4 663	3 300	4 352 612 262	8 263 878	300 736
Rental, property service and travel	4 672	194	1 511 577 160	5 227 082	791 117
Health and social care	1 106	10 605	90 910 202	707 105	167 140
Law and business	5 089	301	308 429 000	884 441	240 064
Entire sample	50 665				

8.2 Appendix 2. Mantissa tests for Benford's Law

Table 8: Ideal Mantissa variables.

Average	0,5
Variance	1/12
Skewness	0
Kurtosis	-6/5

Table 9: Mantissa test results for different industries.

Industry	**Average**	**Variance**	**Skewness**	**Kurtosis**
Other service activity	0,49	0,08	0,07	-1,22
Construction	0,51	0,08	-0,01	-1,16
Property	0,50	0,09	-0,01	-1,25
Motor vehicles	0,50	0,08	0,01	-1,21
Hotels and restaurants	0,50	0,08	0,01	-1,21
Information and communication	0,50	0,08	0,03	-1,21
Culture and leisure	0,49	0,08	0,04	-1,21
Production	0,50	0,09	0,01	-1,24
Transport and storage	0,51	0,09	-0,06	-1,22
Rental, property service and travel	0,50	0,08	0,01	-1,19
Health and social care	0,49	0,09	0,05	-1,29
Law and business	0,49	0,08	0,07	-1,22

8.3 Appendix 3. Key performance indicators for the industries

Data gathered from Retriever Business on the same sample as the one analyzed using the Jones Model.

Table 10: Descriptive statistics (industry mean)

Industry	**# of companies**	**Operating margin (%)**	**Solidity (%)**	**Cash liquidity (%)**	**Balance sheet total (TSEK)**	**Equity (TSEK)**
Other service activity	611	-0,65	37,82	249,48	2 273	824
Construction	792	-5,92	34,74	249,34	5 282	1 426
Property	209	-9,78	32,47	264,09	49 307	8 409
Motor vehicles	3 016	-5,59	36,89	194,42	18 869	7 186
Hotels and restaurants	4 738	-5,76	27,74	216,99	9 554	2 755
Information and communication	529	-18,96	42,21	306,77	11 867	2 378
Culture and leisure	805	-12,55	39,26	280,56	17 613	5 060
Production	1 435	-7,80	39,40	209,25	145 027	32 820
Transport and storage	1 239	-8,94	26,63	313,85	41 840	15 828
Rental, property service and travel	1 185	-16,17	34,89	313,10	16 343	4 558
Health and social care	430	-1,04	47,18	615,56	9 354	3 190
Law and business	1 751	-11,23	37,13	332,12	10 705	3 554
Entire sample	16 740	-14,26	31,37	352,70	22 620	6 247

All numbers as of 2020.

8.4 Appendix 4. Descriptive statistics for the Jones Model

Table 11: Descriptive statistics for the Jones Model residuals

This table shows the descriptive statistics for 2019 and 2020 used in the Jones Model. Standard deviation, median and mean is presented, as well as the number of companies in each industry.

Industry	# of companies	St.dev 2019	Median 2019	Mean 2019	St.dev. 2020	Mean 2020	Median 2020
Other service activity	611	0,157	0,064	0,115	0,167	0,128	0,083
Construction	792	0,219	0,125	0,189	0,172	0,170	0,120
Property	209	0,190	0,043	0,105	0,143	0,102	0,049
Motor vehicles	3 016	0,211	0,083	0,134	0,165	0,131	0,087
Hotels and restaurants	4 738	0,226	0,077	0,116	0,193	0,123	0,085
Information and communication	529	0,313	0,131	0,204	0,237	0,177	0,111
Culture and leisure	805	0,176	0,086	0,143	0,193	0,148	0,098
Production	1 435	0,178	0,075	0,116	0,143	0,112	0,074
Transport and storage	1 239	0,190	0,087	0,129	0,119	0,122	0,088
Rental, property service and travel	1 185	0,591	0,112	0,205	1,197	0,222	0,123
Health and social care	430	0,115	0,062	0,095	0,209	0,153	0,107
Law and business	1 751	0,232	0,100	0,170	0,252	0,196	0,135

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