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The Relationship between Fraudulent Financial Statements, Variations from Benford's Law, and SEC Punishments

ANTOINETTE MCFARLAND
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Reviewed and approved* by the following:

Samuel Bonsall
Associate Professor of Accounting
Honors Adviser and Thesis Supervisor

Brent Schmidt
Assistant Professor of Accounting
Faculty Reader

* Electronic approvals are on file.

ABSTRACT

This thesis researches the impact of variations from Benford's Law on fraudulent financial statements and SEC punishments fraudulent companies received. Benford's Law is used by forensic accountants to detect potential fraud in financial statements. Specifically, forensic accountants use the law to find outliers in a data set by looking at the leading digit in each number. Altered numbers are unlikely to follow Benford's Law, so if a dataset does not adhere to the law, it is possible the dataset was fraudulently manipulated.

I researched Benford's Law to see if there is any other information about financial fraud that forensic accountants can discover using Benford's Law. I analyzed how deviations from Benford's Law relate to the punishment fraudulent firms receive from the SEC, the reported revenue size of each fraudulent company, and the fraud size. Understanding Benford's Law's impact on these three variables can help a forensic accountant better analyze potentially fraudulent financial statements.

In addition, I researched the relationships between punishments from the SEC, revenue size, and fraud size. Understanding how these three variables impact each other can be useful in financial statement analysis and predicting fraud. Forensic accountants can use historical data about past fraud cases to understand how future fraud cases might occur. If forensic accountants can predict the likelihood of a company reporting fraudulent financials, they can stop a fraud early in its stages.

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Chapter 1

Background on Benford's Law

Benford's Law is a statistical law used by forensic accountants to detect potential fraud in financial statements. This method finds outliers in a dataset by looking at the leading digit in each number. Typically, Benford's Law can indicate if a data set was manipulated because the altered numbers are unlikely to follow the natural law.

To provide a brief history, Benford's Law was originally researched by Simon Newcomb in the 1800s. He discovered that pages in the beginning of the book were more worn than pages at the end of the book; this piqued his interest in the phenomenon. Frank Benford then further studied this phenomenon and developed Benford's Law in the 1930s. The Law is still being studied and analyzed, and it was not applied to forensic accounting until the 1990s. It is still a relatively new fraud detection technique but a very useful method for analyzing potentially fraudulent financial statements.

Benford's Law is important because fraud detection has serious implications for the ethics and integrity of businesses across all fields. Additionally, measuring the effects of fraud detection methods could provide information useful to forensic accountants when analyzing financial information for fraud. As criminals become increasingly stealthy about committing fraud, forensic accountants need to find new fraud detection techniques to seek out fraud that has been covered up.

Benford's Law has the potential to be relevant to the forensic accounting community, so it is important to test if the statistical measure can detect anything besides the presence of a fraud. If so, Benford's Law can provide multiple pieces of information for forensic accountants that help make investigations easier and more informative. Equally important is the understanding of what Benford's Law cannot detect, as forensic accountants will need to find other methods of detecting the information that Benford's Law cannot provide.

Through my research, I want to answer the following question: Is there a relationship between deviations from Benford's Law in fraudulent financial statements, the type of financial statement that was fraudulent, and the severity of punishment the firm received from the SEC? It would be beneficial to test what additional information, if any, Benford's Law can provide a forensic accountant.

My hypothesis is that the more a company's financials deviate from expectations arising under Benford's Law, the more significant the fraud is and, therefore, the larger the punishment is. Additionally, I examine the impact that the type of financial statement that was defrauded has on the deviation from Benford's Law and punishment fraudulent companies receive. I predict that companies that commit income statement frauds will receive the greatest punishment from the SEC and vary the most from Benford's Law. I expect that companies that commit statement of cash flows frauds will receive the smallest punishment from the SEC and vary the least from Benford's Law. I researched literature on Benford's Law to see if I will confirm or refute my hypothesis, and I found some mixed data that indicates I may confirm or refute my hypothesis; there is no clear answer to my question yet.

There is a lot of research and information about Benford's Law and its application to forensic accounting. However, there is no prior research that specifically examines the relationship between deviations from Benford's Law and the severity of punishment that companies received nor about how Benford's Law applies to specific financial statements.

Rather, Benford's Law was just used as a mechanism to detect potential fraud, and then forensic accountants further investigated the fraud and how severe the misstatements were.

Amiram, Bozanic, and Rouen (2015) argues that there are advantages to using Benford's Law over other types of detection methods, both conceptual and statistical. In the study, the authors researched misstated and restated financial statements, and found that when the mistakes were fixed the financial statements more closely followed Benford's Laws than the initial financial statements. Additionally, the research found that earning persistence decreased as divergence from Benford's Law decreased. This does indicate that the amount of divergence could be related to the significance of fraud or misstatements, as the article is arguing that the significance of divergences relates to the quality of earnings information.

Association of Certified Fraud Examiners (2018) provides an overview of the research on using Benford's Law in forensic accounting. This guide shows that there are five types of tests using Benford's Law. This explains that some are high-level tests, and if a company's financials does not pass these tests then a forensic accountant can look at the first and second digit together in a test to detect potential fraud. There is also a test to detect errors in rounding, which could additionally indicate fraud. This guide also shows that the significance of deviations from Benford's Law is important in determining whether there is potential fraud or not. Because the significance of the deviation matters, that would support my hypothesis that the more significant the deviation, the more significant the fraud. It is obvious that if there is no deviation from Benford's Law, there is no suggestion of fraud, however it is not obvious that if there is a significant deviation, that means the level of fraud is more severe.

Durtschi et al. (2004) discusses how to effectively use Benford's Law in detecting fraud. This article made an excellent argument about why only certain types of fraud may be detected using Benford's Law; only specific types of accounting numbers may be fraudulent when they deviate from Benford's Law. Duplicates, for example, cannot be detected through Benford's Law. This article recommends using Benford's Law as a general tool to detect fraud, and then focusing on finding specific fraud through other detection techniques. This article indicates that my hypothesis might be wrong, because there may be types of fraud that are not detected by Benford's Law, so the deviation from Benford's Law may not relate to the severity of fraud.

Diekmann (2007) covers the way to use Benford's Law in detecting fraud in scientific data. Although this article did not research financial data, it does show some interesting findings about the use of Benford's Law in detecting fraud in any kind of data. This article recommended using other digits besides the leading digit to detect potential fraud, since the first digit only shows generic patterns, but the other digits show more statistically significant patterns. Although this research does not relate to Benford's Law's capabilities, it does influence the conclusion I come to, and my recommendation for further research into the second or third leading digit.

Finally, Bhattacharya, Sukanto, and Kuldeep (2008) spotlighted forensic accounting and provided a generic overview of Benford's Law. The authors explained that forensic accountants can use Benford's Law as a goodness of fit test to detect fraud, but deviations from Benford's Law do not automatically mean that financial statements are fraudulent. Financial statements may have mistakes, or just vary from Benford's Law, so additional research must be conducted to determine if deviations from the law are due to fraud or other reasons. This shows that my hypothesis may be incorrect, because Benford's Law does not specifically show fraud, it may show other errors in the financials.

There is a significant amount of research available about Benford's Law and its application to fraud investigation and forensic accounting. However, the research shows conflicting predictions about Benford's Law's ability to predict how severe fraud is or if there is a link to the financial statements impacted. Through my research, I want to confirm or refute my hypotheses, and encourage researchers to continue to examine Benford's Law and other fraud detection techniques.

Chapter 2

Research on Punishment, Revenue, and Fraud-Size and FSD Score

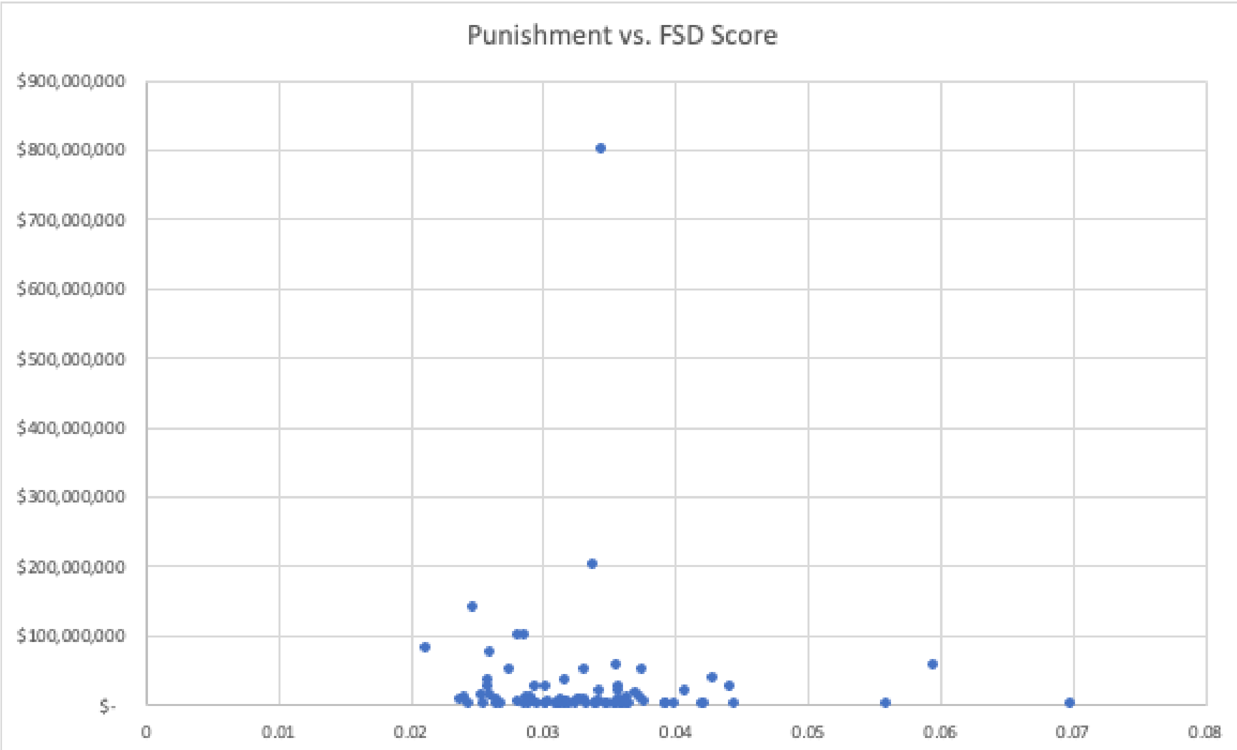
To conduct research on the statistical advantages of Benford's Laws, I collect data from Wharton Research Data Services (WRDS) and NYU Securities Enforcement Empirical Database (SEED). From WRDS I access the GV key of each company analyzed. I link that key to the data I collected from NYU SEED, which contains the punishment and fraud size of the various firms. I find the revenue size from a variety of sources including SEC filings. Finally, I find the Forecasted Standard Deviation (FSD) score, which is available from the research conducted by Amiram et al. (2015). This score measures the financial statements divergence from Benford's Law and is what I use to find a correlation between Benford's Law and various other measures.

NYU SEED provides information about a variety of SEC cases from 2002 to 2021. Since the data with Benford's Law ranges from 1990 to 2016, I limit my search in SEED to that time frame.

Punishment Relationship to FSD Score

In Excel, I recorded the punishment the firm received and use a VLOOKUP function to match the punishment each firm receives to the average of the FSD scores for that firm from the most available data to the year of the fraud. From there, I run a correlation test using Excel's CORREL function to see the connection between the punishment the firm received to the deviation from Benford's Law. The correlation is 0.054. Figure 1 below shows the relationship between punishment and FSD score and that there is no significant correlation.

Figure 1: The Relationship Between Punishment and FSD Score



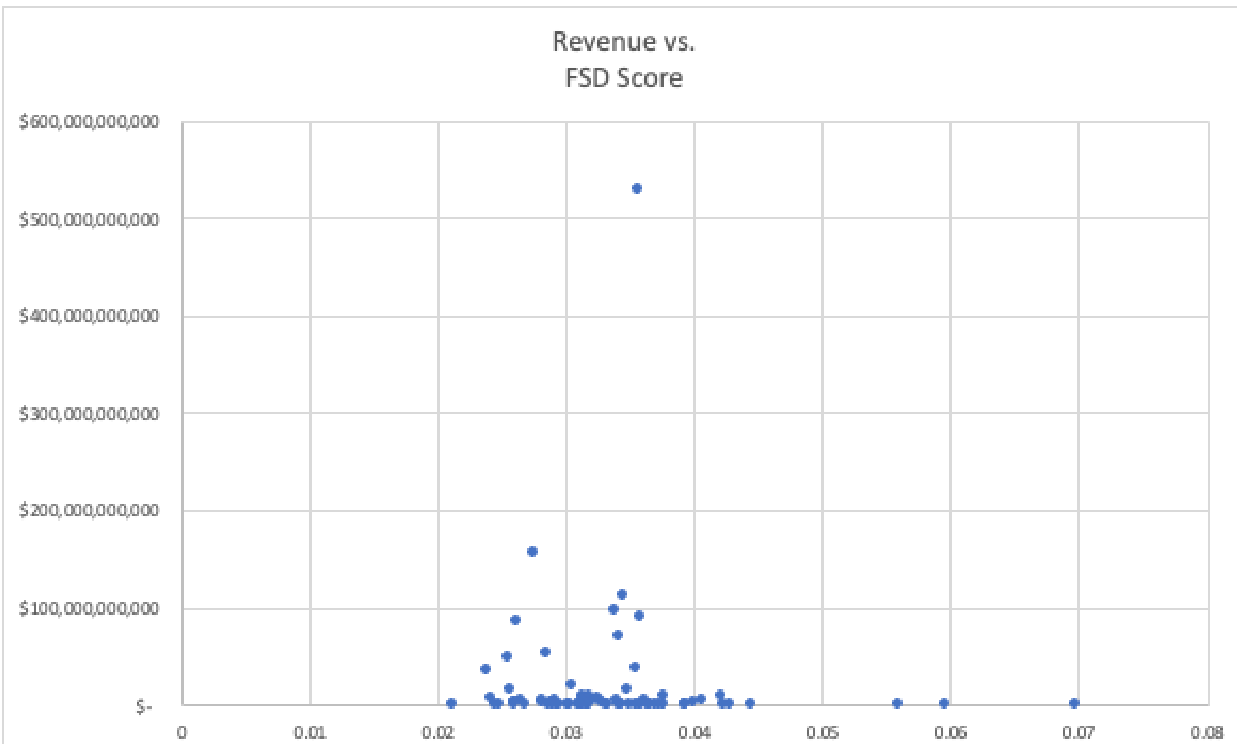
This table shows the distribution of the FSD scores compared to punishment, showing no significant correlation

After conducting a regression analysis on the impact the punishment has on the FSD score, with the FSD score as the independent variable, the calculated P-value for the intercept is 0.409. The P-value is higher than 0.05, meaning that we can fail to reject the null hypothesis of no relationship between deviation from Benford's Law and firm punishments.

Revenue and Fraud Size Relationship to FSD Score

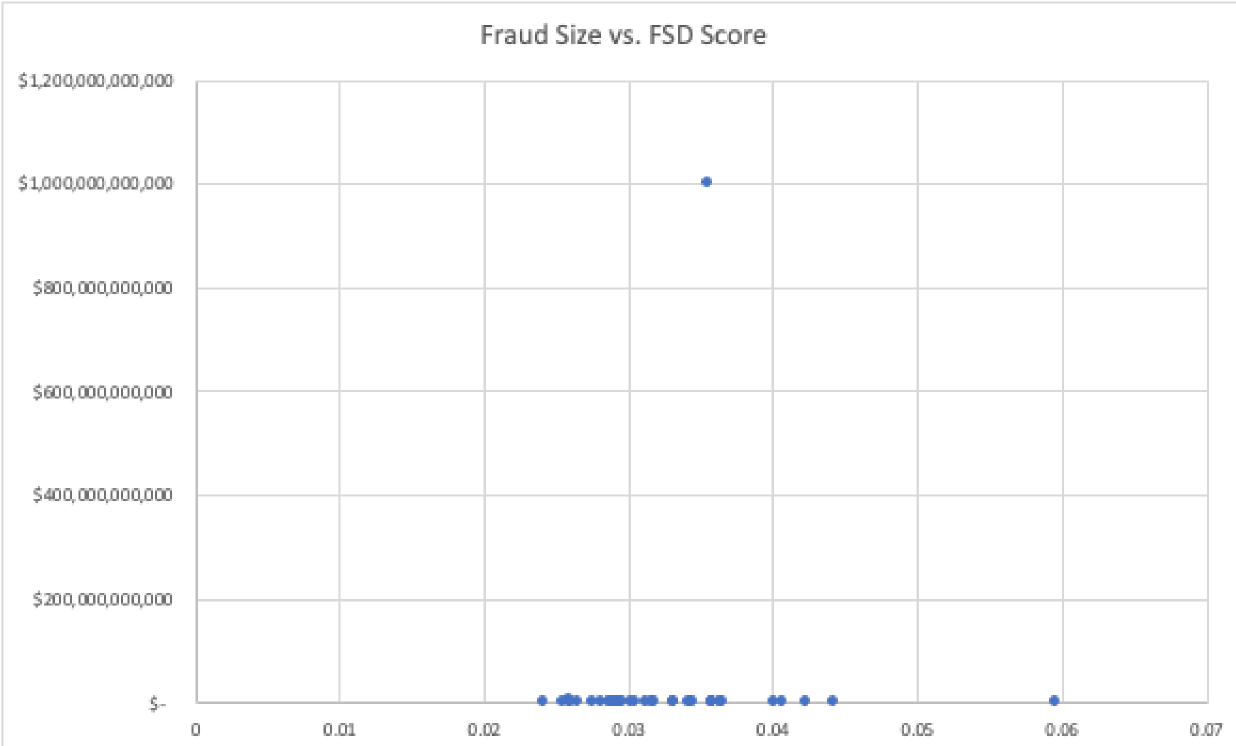
To test other aspects of Benford's Law, I examined whether Benford's Law could predict either revenue size or fraud size. The revenue size is the reported revenue of each firm while the fraud size is the monetary amount of misstatement on the financial statements. I used the same method as explained above to find the relationship between the revenue size of the fraudulent companies and Benford's Law. In addition, the same method was used to see if there was a correlation between the fraud size and the deviation from Benford's Law. The correlation between the FSD score and the revenue size is 0.008. The correlation between the FSD score and the fraud size is 0.065. Figures 2 and 3 below show the graphical relationship between revenue and FSD score and fraud size and FSD score.

Figure 2: The Relationship Between Revenue and FSD Score



This table shows the FSD scores compared to Revenue distribution, showing no significant correlation

Figure 3: The Relationships Between Fraud Size and FSD Score



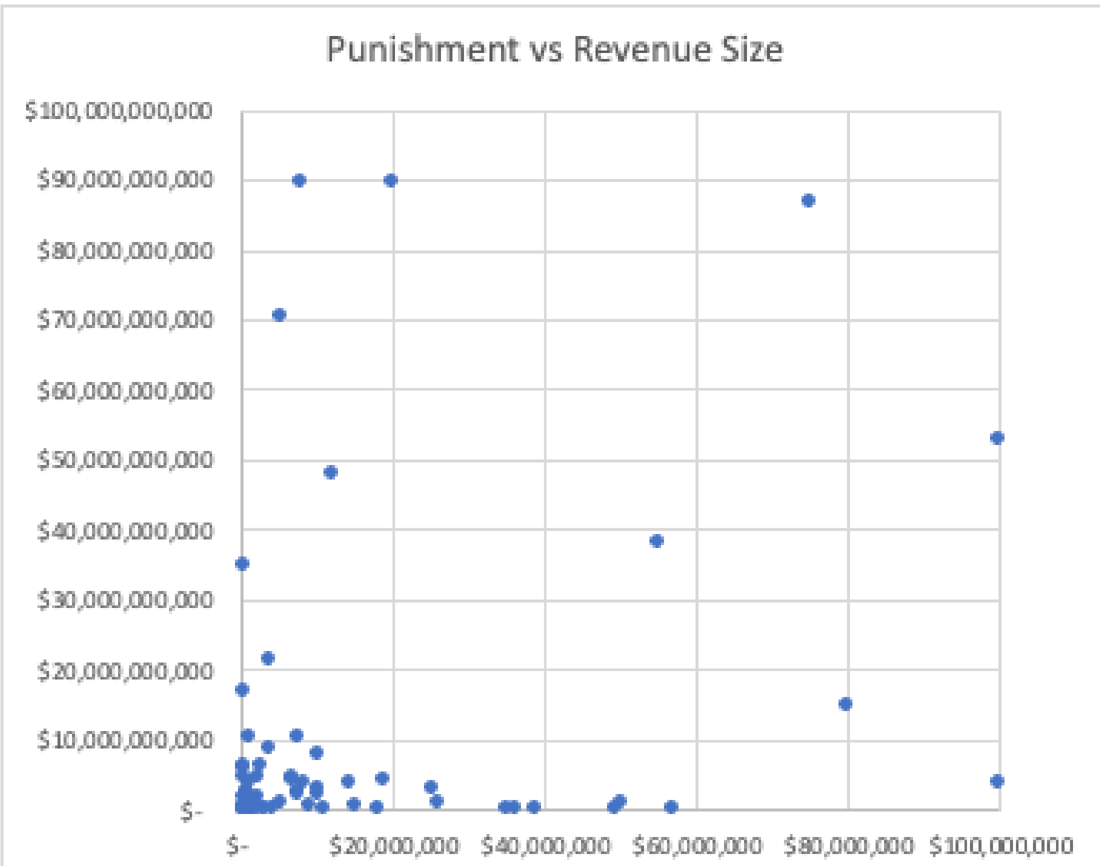
This table shows the fraud size compared to the FSD score, showing no significant correlation

A regression analysis on the impact the fraud and revenue size on the FSD score reveals a P-value for the intercepts of 0.844 and 0.406. The null hypothesis is that there is no relationship between the two variables. Since the P-value is higher than 0.05, I fail to reject the null hypothesis. This supports the correlation analysis since I am unable to detect a statistically significant association between either fraud size and the FSD score or revenue size and the FSD score.

Punishment, Fraud-Size, and Revenue Relationship

Finally, I examine if the punishments, fraud size, or revenue size are related. Based on that investigation, I find that the correlation between punishment and revenue size is the highest at 0.197. Figure 4 below graphically shows the relationship between punishment and revenue size.

Figure 4: The Relationship Between Punishment and Revenue Size

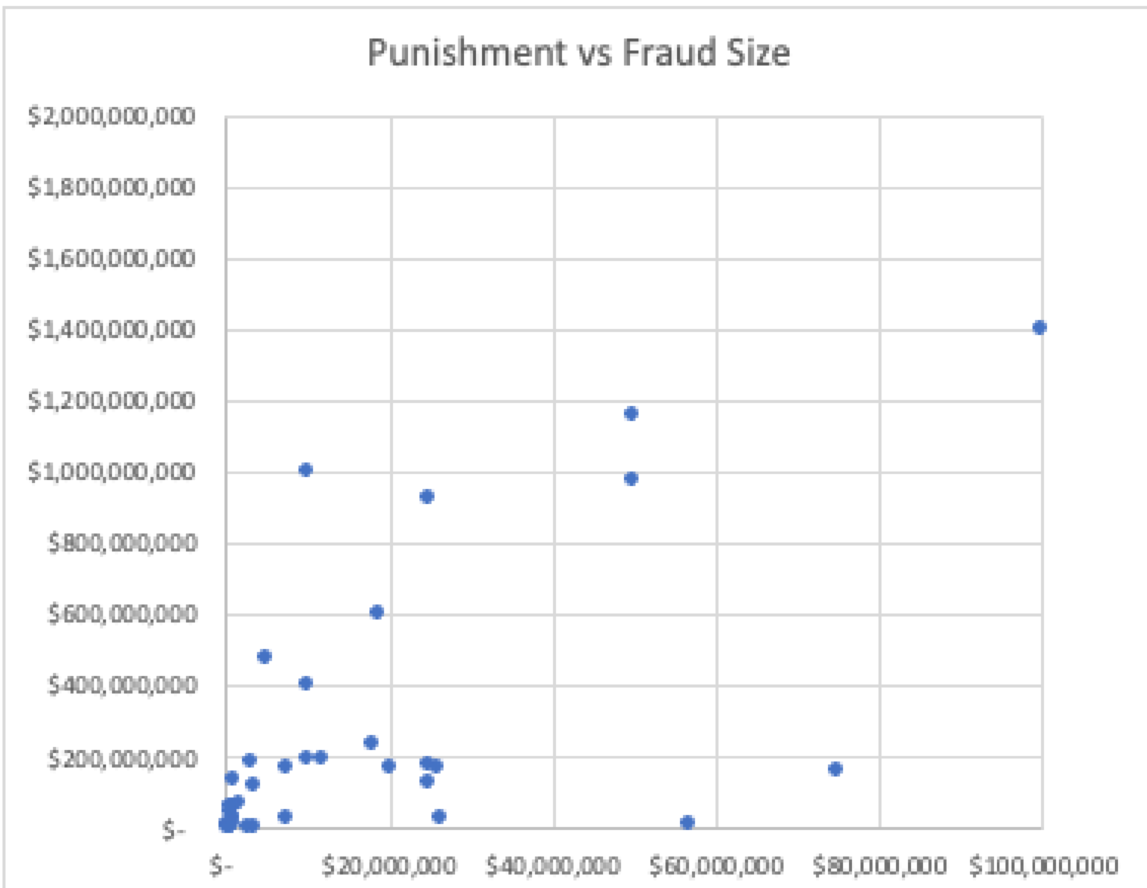


This table shows the relationship between punishment (x-axis) and revenue size (y-axis), showing no significant correlation

Using a regression analysis of the relationship between punishment and revenue size, I calculate a P-value of 0.081. However, this is still not statistically significant and does not indicate a strong correlation between punishment and revenue size.

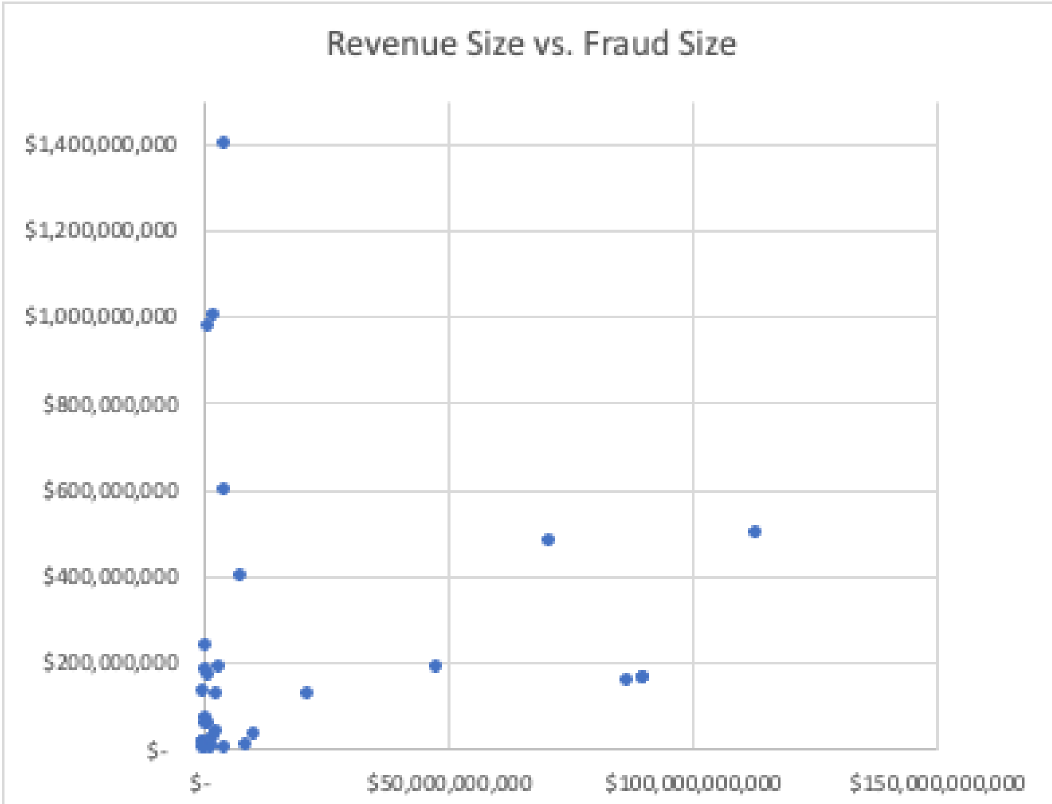
Next, the correlation between punishment and fraud size is insignificant at 0.022, and the correlation between revenue and fraud size is insignificant at 0.070. Both relationships are represented graphically in Figure 5 and Figure 6 below.

Figure 5: The Relationship Between Punishment and Fraud Size



This table shows the relationship between the punishment and fraud size, showing no significant correlation

Figure 6: The Relationship Between Revenue and Fraud Size



This table shows the relationship between revenue and fraud size, showing no significant correlation

The lack of correlation between punishment and fraud size and revenue and fraud size is supported by a regression analysis, which yields P-values of 0.894 and 0.688 respectively. Both p-values are higher than 0.05, meaning that I fail to reject the null hypothesis. I expect there to be no relationship between punishment and fraud size or revenue and fraud size.

Table 1 below summarizes the statistical analyses in this chapter, showing the lack of statistical significance between the FSD score and the three variables punishment, revenue, and fraud-size.

Table 1: The Statistical Analysis of the Relationships Between Punishment and FSD Score, Revenue and FSD Score, and Fraud-Size and FSD Score

	Punishment	Revenue	Fraud-Size
Intercept t-Stat	0.829	0.836	-0.197
Intercept p-Stat	0.409	0.406	0.845
R Square	0.0008	0.0010	0.0042
Observations	85	78	39

This table shows the t-stat intercept, p-stat intercept, r square, and number of observations for the regressions involving FSD score and the punishment, revenue, and fraud-size

Although the associations between the main variables of interest are not statistically significant at conventional levels, my findings can still prove to be insightful for forensic accounting. The lack of correlation between the punishment firms receive and the FSD scores indicates that Benford's Law cannot be used to predict how firms are punished for committing fraud. This could be because punishments vary significantly by court cases; the lawyers' strategies can influence if a firm receives a significant or less significant punishment. Each fraud also varies too, which influences the amount of punishment a firm receives.

Next, the lack of a relationship between the revenue size and the FSD score of a firm is logical. There does not seem to be a connection between a firm's size and its likelihood to commit fraud.

In addition, the small correlation between the fraud size and FSD score continues to suggest that Benford's Law cannot be used to detect the severity of the fraud. Although each individual fraud's court case affects the punishment the firm receives, the monetary misstatement of each fraud does not experience the same bias the punishment does. In addition, the monetary misstatements are typically estimated, and can be a combination of multiple frauds. Since there is no uniform way to estimate monetary misstatement, it is logical that there is no correlation between the misstatement and FSD score.

Finally, the lack of significant correlation between the punishment, revenue, and fraud size indicates that there is potential bias in the punishment a firm receives. It also supports the idea that the measure of fraud can vary case by case, and there is no uniform way to estimate the amount of fraud a corporation commits.

This information can be useful when conducting investigations. It is important to know the limits of Benford's Law so that accountants can continue to look for other ways to estimate and predict the severity of a corporation's fraud.

We should continue to look for other methods of predicting the severity of fraud. If there is a significant deviation from Benford's Law, it does not necessarily mean that there is fraud, or that it is significant. Also, just because there is no deviation from Benford's Law, there could still be fraud occurring; this is important to understand so that frauds are not overlooked because they do not fail certain tests.

Chapter 3

The Relationship Between Fraud and Financial Statements

In the second part of my research, I explore the various fraud cases and what financial statement is mainly impacted by the fraud. I look at both the relationships between the statements and FSD score and the statements and punishment companies received. 79.55 percent of the frauds affected the income statement most, 18.18 percent of the frauds affected the balance sheet most, and 2.27 percent of the frauds affected the statement of cash flows most.

Income Statement Relationship to FSD Score

Since there are a significant number of frauds affected by the income statement, I decided to compare each type of financial statement to itself, rather than the other two. The income statement is relatively evenly spread among all the FSD scores. 25.7 percent of all the income statement frauds occur in the top 25 percent of FSD scores (ranged 0.02113-0.02855), 31.4 percent in the 0.02871-0.03120 range, 22.9 percent in the 0.3124-0.0343 range, and 20 percent in the 0.03481-0.06983 range. (Note: each range covers 25 percent of the total frauds).

Balance Sheet and Statement of Cash Flows Relationship to FSD Score

The balance sheet is less evenly spread among all the FSD scores, mainly affecting less severe FSD scores. 12.5 percent of all the balance sheet frauds occur in the top 25 percent of FSD scores, 0 percent in the 25-50 percent range, 37.5 percent in the 50-75 percent range, and 50 percent in the 75-100 percent range. There was only one statement of cash flows fraud, which occurs in the top 25 percent. Tables 2, 3, and 4 below summarizes the findings when analyzing the FSD score impact on the type of financial statement.

Table 2: The Relationship Between the Range of FSD Scores and the Count of Frauds Affecting Each Type of Financial Statement

FSD Score Range	Income Statement Count	Balance Sheet Count	Statement of Cash Flows Count
0.02113-0.02855	9	1	1
0.02871-0.03120	11	0	0
0.03124-0.0343	8	3	0
0.03481-0.06983	7	4	0

This table shows the count of the frauds that affect each type of financial statement across a range of FSD scores

Table 3: The Relationship Between the Range of FSD Scores and the Percent of Frauds Affecting Each Type of Financial Statement Across All Three Financial Statements

FSD Score Range	Income Statement Percent of All Financial Statements	Balance Sheet Percent of All Financial Statements	Statement of Cash Flows Percent of All Financial Statements
0.02113-0.02855	82%	9%	9%
0.02871-0.03120	100%	0%	0%
0.03124-0.0343	73%	27%	0%
0.03481-0.06983	64%	36%	0%

This table shows the percent of the frauds out of all three financial statements that affect each type of financial statement across a range of FSD scores

Table 4: The Relationship Between the Range of FSD Scores and the Percent of Frauds Affecting Each Type of Financial Statement For Each Individual Financial Statement

FSD Score Range	Income Statement Percent of Total Income Statement	Balance Sheet Percent of Total Balance Sheet	Statement of Cash Flows Percent of Total Statement of Cash Flows
0.02113-0.02855	26%	13%	100%
0.02871-0.03120	31%	0%	0%
0.03124-0.0343	23%	38%	0%
0.03481-0.06983	20%	50%	0%

This table shows the percent of the frauds for each individual financial statement across a range of FSD scores

Above, I examine the relationship between the range of FSD scores and financial statement affected by the fraud. Below, I compare the punishment a fraudulent firm receives to the financial statement impacted.

Income Statement Relationship to Punishment

I also measure the relationship between the punishment received by the SEC and the financial statement affected by the fraud. Like with FSD score, the income statement is relatively evenly spread among all of punishments. 22.9 percent of all of the income statement frauds occur in the top 25 percent of punishments (ranged from $35 million to $800 million), 28.6 percent in the $10 million to $27 million range, 25.7 percent in the $1.75 million to $9 million range, and 22.9 percent in the $150,000 to $1.5 million range.

Balance Sheet and Statement of Cash Flows Relationship to Punishment

The balance sheet is also relatively evenly spread among all the punishments but is more concentrated with the more significant punishments. 37.5 percent of all the balance sheet frauds occur in the top 25 percent of punishments, 12.5 percent in the 25-50 percent range, 25 percent in the 50-75 percent range, and 25 percent in the 75-100 percent range. There was only one statement of cash flows fraud, which occurs in the bottom 25 percent. Tables 5, 6, and 7 below summarizes the findings.

Table 5: The Relationship Between the Range of Punishments and the Count of Frauds Affecting Each Type of Financial Statement

Punishment Range	Income Statement Count	Balance Sheet Count	Statement of Cash Flows Count
$35 million to $800 million	8	3	0
$10 million to $27 million	10	1	0
$1.75 million to $9 million	9	2	0
Below $1.5 million	8	2	1

This table shows the count of the frauds that affect each type of financial statement across a ranges of punishments

Table 6: The Relationship Between the Range of Punishments and the Percent of Frauds Affecting Each Type of Financial Statement Across All Three Financial Statements

Punishment Range	Income Statement Percent of All Financial Statements	Balance Sheet Percent of All Financial Statements	Statement of Cash Flows Percent of All Financial Statements
$35 million to $800 million	73%	27%	0%
$10 million to $27 million	91%	9%	0%
$1.75 million to $9 million	82%	18%	0%
Below $1.5 million	73%	18%	9%

This table shows the percent of the frauds out of all three financial statements that affect each type of financial statement across a ranges of punishments

Table 7: The Relationship Between the Range of Punishments and the Percent of Frauds Affecting Each Type of Financial Statement For Each Individual Financial Statement

Punishment Range	Income Statement Percent of Total Income Statement	Balance Sheet Percent of Total Balance Sheet	Statement of Cash Flows Percent of Total Statement of Cash Flows
$35 million to $800 million	23%	38%	0%

$10 million to $27 million	29%	13%	0%
$1.75 million to $9 million	26%	25%	0%
Below $1.5 million	23%	25%	100%

This table shows the percent of the frauds for each individual financial statement across a ranges of punishments

From my analysis, the financial statement most impacted by fraud is the income statement. The key metrics in the income statement are revenue and net income, both of which could affect stockholders' views of a company. It is understandable that these values would be reported falsely; faking revenues can make a company look financially healthier than it actually is.

In addition, it is interesting that the income statement seems to be spread relatively evenly among each range of FSD scores and punishments. This does not support my hypothesis, because I predicted that the income statement would deviate the most from Benford's Law. I also predicted that income statement frauds would result in the most significant punishments from the SEC. The balance sheet seems to mostly affect the FSD scores greater than 0.03124 and affect punishments greater than $35 million. This could indicate that greater deviations from Benford's Law are more likely to impact the balance sheet than smaller deviations from Benford's Law. It could also indicate that balance sheet fraud is punished severely by the SEC.

The statement of cash flows is not impacted by fraud as often as the income statement or balance sheet are. The statement of cash flows may not be as important to investors as the income statement or balance sheet. Additionally, it could be more difficult to detect fraud in the statement of cash flows, which is why it is not recorded as fraud as often. Or, it could be more difficult for fraudsters to manipulate the statement of cash flows. This analysis shows that forensic accountants should look more closely into statement of cash flows frauds and how to detect them.

When analyzing financial fraud cases, it is critical to analyze the financial statements that are affected by the fraud. This can help forensic accountants decide the best way to look for fraud in each financial statement, as it may look different in each financial statement.

Chapter 4

Conclusion

When evaluating the relationship between variables, it is important to recognize that there may be no significant relationship. Understanding the limitations of statistical measures allow us to explore other ways to get desired valuations. Although Benford's Law has been found to be very helpful in predicting if a company's financial statements are fraudulent, it does not appear to predict the severity of the fraud or the financial statement affected. Forensic accountants can look for other statistical measures that may be helpful in predicting the severity of fraud or financial statements affected by fraud.

I would recommend forensic accountants further analyze the capabilities and limitations of Benford's Law. Forensic accountants could test how Benford's Law relates to key accounts on financial statements, like revenue and income, which could be useful in detecting financial statement fraud.

Additionally, forensic accountants should research how and if fraudsters try to cover up their fraud by adhering to Benford's Law. Although it is important to understand Benford's Law as a statistical law, it is equally important to understand its application in fraud detection and how fraudsters may use Benford's Law to their advantage.

Forensic accountants should also further research the relationship between fraud size, revenue size, and punishment size. This can help forensic accountants in valuing the materiality of misstatements. In addition, I learned through my research that there is no uniform way to value the severity of fraud. Some ways to measure fraud include the punishment received, changes in financial restatements, and the dollar amount misstated on the financials. But it could be useful to create a method for such valuation to help researchers when studying fraud detection.

Overall, forensic accountants have an exciting opportunity to conduct more research on fraud detection techniques, including Benford's Law. As fraudsters continue to learn more about ways to commit fraud, forensic accountants must keep up by discovering new ways to detect and prevent fraud.

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ACADEMIC VITA

Antoinette (Toni) McFarland

EDUCATION

The Pennsylvania State University, University Park, PA Intended Graduation: December 2021
Schreyer Honors College, Smeal College of Business
Integrated Master of Accounting, Bachelor of Science in Accounting
University of Sussex, Brighton, UK *July 2019-August 2019*
International Summer School
British Film

LEADERSHIP EXPERIENCE

University Park Undergraduate Association **University Park, PA**
Executive Director of Finance *November 2020 – Present*
- Manage $150,000 budget allocated from Student Fee Board dollars, donations, and organization fundraising efforts
- Consult regularly with Deputy Director on current financial projects, including check requests and UPUA bills
- Ensure financial transparency through creating Deputy position, regular communication, and creating a public budget

Schreyer Honors College Student Council **University Park, PA**
Merchandise Committee Chair (September 2018 – April 2019), Treasurer (April 2019 – May 2021) *September 2018 – Present*
- Budgeted over $10,000 on Microsoft Excel and handle Associated Student Activities account to fund events for scholars
- Designed and sold Schreyer merchandise online and at various Schreyer events throughout the year, promoting student pride
- Facilitated bi-weekly committee meetings focused on improving merchandise designs, sales, and website

The Sapphire Leadership Academic Program **University Park, PA**
Active Member *August 2018 – Present*
- Recruited to represent the top 5% of Smeal College of Business students in an academic program that engages students in specialized curricula to develop outstanding leadership skills
- Engaged in academically rigorous Sapphire courses to replace general business curriculum courses
- Participate in professional and leadership development and community involvement events, to become more well-rounded

Schreyer Honors Orientation (SHO) TIME **University Park, PA**
Community Builders and Finale Collaboration Mentor *October 2018 – August 2019*
- Organized three-day orientation for 300 incoming first-year Scholars to acclimate students to the Schreyer Honors College
- Lead 10 students through various activities with an expressed passion and excitement for Honors College to inspire students
- Developed and planned Playfair and Finale events; acted as a stage manager during the finale, ensuring students' enjoyment

Penn State Sociology Department **University Park, PA**
Teaching Assistant *January 2020 – May 2020*
- Assessed students' essays to ensure they are complete, accurate, and thoughtful and provided feedback to improve work
- Communicated to professor main themes found in assignments to tailor his class to the interests of the current students

ACCOUNTING EXPERIENCE

EY **Philadelphia, PA**
Forensics Intern (June 2021 – August 2021), Forensics Staff (Starting Fall 2022) *June 2021 – August 2021*
- Worked on multiple forensics projects covering a wide variety of subjects including investigations and insurance claims
- Developed professional skills including Excel through client engagements, meeting with EY employees, and online learnings

Volunteer Income Tax Assistance **University Park, PA**
Tax Preparer (December 2019 – April 2020), Secretary (April 2020 – May 2021) *December 2019 – Present*
- Educate 1-4 Centre County residents weekly by offering a free tax return service for federal, state, and local taxes
- Maintain a professional relationship with clients to ensure their returns are as accurate as possible, helping them save money
- Earned Standards of Conduct, Intake, Basic, and Advanced certifications to effectively and correctly file returns

Penn State Accounting Department **University Park, PA**
Accounting 211 TA (January 2021 – May 2021), Accounting 803 TA (August 2021 – Present) *January 2021 – Present*
- Created and lead review 90-minute sessions for Accounting 211 Honors students to prepare for each exam
- Offered office hours to Accounting 211 students so they could ask questions about the class and go through practice problems
- Conduct research on current fraud cases for Accounting 803 to work with the professor to create a project for the students

Vanguard **Malvern, PA**
College-to-Corporate Finance and Accounting Intern *May 2020 – July 2020*
- Produced datasheets in Excel to assist Corporate Financial Reporting team with organizing and assessing their reports
- Assisted Vanguard Marketing Corporation with account reconciliations, creating reports, and quarter-end close

HONORS AND AWARDS & SPECIAL INTERESTS

Honors and Awards: Smeal Student Marshal, Dean's List, The President's Freshman Award, President's Sparks Award, Evan Pugh Senior Award, D'Ambrosio Honors Scholarship
Interests: Baking, Reading, Distance Running