THE EFFECT OF DETECTED FINANCIAL REPORTING MISCONDUCT ON GROSS DOMESTIC PRODUCT AND UNEMPLOYMENT IN THE UNITED STATES

by

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The relationship between corporate accounting fraud and macroeconomic downturns represents an enormous opportunity to better understand the landscape of the American market, and yet this remains one of the most under-researched topics in the field. While most modern research focuses on the incentives behind the executives committing fraud, very little has been done in the way of determining how these actions impact greater society both directly and inadvertently in the form of macroeconomic aftermath.

Understanding if and how instances of financial reporting misconduct can be used as a predictor of changes in economic conditions could be an invaluable addition to the toolbox of future economists. Additionally, creating an effective model that predicts the relationship between these variables has the potential to inform consumers by helping to explain how the rate of fraud detection can impact the economy. The following research explores the relationship between financial reporting misconduct and the economy at large.

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Chapter 1: Introduction

This research is all about exploring companies that partake in under-the-table deals, collusion, and effectively lying to their entire user base about the quality of their product. A single arrangement has the potential to make or break an executive's career. This same arrangement can also simultaneously deceive thousands of unwitting individuals in the general public. Millions of dollars are on the line, as the battle between what is truthful and what is profitable is waged on one of the most public stages in the United States.

While this may sound like an excerpt from a high-profile thriller novel, this field of study stems from a domain that seems to be on an entirely different wavelength: accounting. Here we inspect corporate fraud, where the "product" being delivered to the end consumer is the annual financial statements filed with the federal government. These documents, prepared and delivered by the fiduciary agents of the company's management, detail the financial happenings of the company over the fiscal year. The "consumers" of these products are the real owners of the company, the shareholders, who look to these filings for information on how the corporation is performing. The conflicting interests of this principal-agent relationship presents a challenging problem: while management may not have much "skin in the game" in the company's ownership, there is a reasonable expectation of success from shareholders. Failure to meet these expectations may result in negative paygrade or termination.

When a company's performance is subpar, upper management may approach the consequences in a variety of ways. While the vast majority of these actions are legal and in compliance with Generally Accepted Accounting Principles, the one percent I will be researching are those that choose to “fudge the numbers” of their financial statements in order to mislead shareholders and other stakeholders. This is corporate accounting fraud.

My research examines the relationship between detected accounting fraud and future macroeconomic conditions. Intuitively, the detection of fraud results in massive monetary losses for a firm’s shareholders, potentially reducing individual consumption and harming the economy. Fraud detection may also result in decreased consumer confidence in the market, which would also lead to decreased consumption. There may even be an impact on unemployment as firm shareholders in the accused corporation suffer massive losses and potentially lay off employees. These theoretical processes yield the specific question that guided my research: to what extent can the detection of accounting fraud help explain changes in future macroeconomic conditions?

Chapter 2: Methodology

The purpose of this study was to determine whether or not detected accounting fraud can be used to help explain changes in the United States economy, while additional cross-sectional analysis helped determine which aspects of a fraud detection have the greatest impact on economic conditions. I have chosen to limit my analysis to the US to maintain a consistent set of federal regulations regarding fraud detection and also to narrow the scope of economic analysis to control for other variables. The following methods will be implemented to achieve this goal.

Definition of Key Terms

Before gathering data for this research, a clear definition of "financial reporting misconduct" had to be established. The problem with researching fraud and other forms of misreporting is that its occurrence can be difficult to estimate when only a minute fraction of cases are actually discovered. Even then, the intent behind a misstatement can be difficult to discern. "Corporate fraud" can even be somewhat misleading, as not all misconduct results in litigation, and not all fraud cases that go to trial result in convictions. Therefore, the data this research required encompassed misreporting by management that results in material misstatement on the financials. The phrases "financial reporting misconduct" and "corporate fraud" will be used interchangeably to describe this phenomenon.

Definitions for macroeconomic conditions are more clear-cut. The primary measure of a country's economic success is its annual gross domestic product (GDP), which measures the total value of all final goods and services produced within the nation's borders in a given year. The unemployment rate reveals the percentage of unemployed individuals as a percentage of the total workforce. These two measures, although in isolation may vastly under-simplify overall economic health, still provided a mechanism of interpreting the state of the US economy. These were used as the benchmarks for macroeconomic conditions for the sake of my research.

Data Sources

Obtaining data from sources that are reputable, reliable, and accurate was a critical step to ensuring the success of this research. For data on instances of financial reporting misconduct, I used Accounting and Auditing Enforcement Releases (AAERs). These statements are issued by the Securities Exchange Commission (SEC) following an investigation into a company or individual for alleged financial misconduct. The dataset I relied on is a comprehensive database of AAER's dating back to the 1980's that relate to financial reporting misconduct.

A major problem with research into financial reporting misconduct is that there is often a significant delay between the actual occurrence of fraud and the time when it is detected. While the AAER data does include the periods over which fraud occurred, my research is interested in when the fraud was publicly revealed. I expected that the detection and revelation of fraud was more likely to influence consumer behavior and subsequently economic conditions because shareholder losses and consumer confidence likely do not change until the fraud is revealed. For the purposes of this study, I identified the revelation of the fraud as occurring 3 months after the end of the misreporting period.

Using data from the Center for Research in Security Prices (CRSP), I also calculated each firm's market capitalization before and after the fraud was discovered.

The difference between these measures helps describe the loss to investors, as it reflects the total value of stock lost over all of the firm's shares. Although this measure could be calculated by hand-collecting the exact date of fraud discovery, for the purposes of this research I found it sufficient to calculate each firm's market capitalization as of the date the misreporting began and the market capitalization three months after the end of the misreporting period.

Economic data was obtained from a few sources. The Federal Reserve Bank of St. Louis offers an online source FRED (Federal Reserve Economic Data) that provides a user-friendly database for manipulation of variables and data extraction. The site uses reputable government research institutes' data and compiles it into a database sorted into quarterly measurements. Data on unemployment rates was collected by the United States Bureau of Labor Statistics (USBLS), and the data I used for GDP was collected by the United States Bureau of Economic Analysis (USBEA). I accessed both of these data sources through FRED for my analysis.

I also accessed consumer sentiment data through FRED. This program allowed me to download a quarterly measurement of consumer sentiment data collected from the Surveys of Consumers research sector of the University of Michigan. Sentiment data reflects the attitude of consumers towards the state of the economy. This data is based on a baseline score of 100, with higher values reflecting higher consumer sentiment. Consumer sentiment measurements help contextualize economic conditions through consumer perceptions.

I organized all of this data by quarters in the calendar year. Each quarter had a value for the number of instances of accounting fraud revealed and the corresponding change in GDP and unemployment during that period. Unfortunately, different data sources had unique cutoffs for the time periods available for their data, and with the nature of my analysis I could only use observational periods wherein there was data available for all variables. This resulted in a smaller observation pool than would have been available from any of the data sources independently. I collected usable data from years 1980-2012 for my analysis, and aggregating data quarterly I collected a total of 130 observable periods.

Data Analysis and Application

I used the program Statistical Analysis Software (SAS) in conducting my analysis. Given the size and quality of data I retrieved, this software was the most practical option for creating concise results reports.

Before diving into the details of using SAS for this particular model, it's important to understand how linear regression equations are useful for research that gauges the strength of relationship between two variables. This relationship, though generally descriptive for past observations, are even more useful in that they can allow for future prediction of the variables if their relationship is strong enough. Basically, this software takes observed data and aggregates it into an equation that can predict future values based on past values. The software also automatically calculates statistical values that measure the strength of the relationship between variables, which is what I used to determine if there is a significant negative relationship between instances of accounting fraud and GDP.

While I didn't necessarily expect the detection of a singular fraud to result in a massive economic downturn, this analysis was aimed at determining if the amount of fraud detection in a given period may slow the growth of GDP in the following period. In the form of the simple linear equation $Y = x + b$[1], the Y output I examined was the percent change in GDP from the following period. The independent variable was the measured instances of corporate accounting fraud for the period, and the remaining variables were controls to help capture factors that may be behind any discovered changes in GDP. I controlled for GDP in the quarter the fraud was revealed by lagging the variable by one period as an additional variable.

A secondary test examined a similar relationship, but with the change in unemployment rate as the dependent variable. This equation attempted to model the relationship between detected financial reporting misconduct and a change in the unemployment rate.

I performed additional cross-sectional analysis to determine how different characteristics of a fraud detection may influence the severity of its impact on the economy. One such characteristic I chose to examine was consumer sentiment. I expected that if consumer confidence is already low at the time of the detection, its impact will be more severe as consumption is driven down even further.

Examining this variable required the inclusion of an interaction variable to my previous simple linear regression equation. An interaction variable measures how the addition of another variable into a model influences the relation between the dependent variable and an explanatory variable in the model. This shows both how the variable itself impacts the equation and also explains how well the two variables interact with

[1]In this equation and the ones following, I have simplified the regression equation for ease of reading for individuals unfamiliar with stats analysis. This simplified equation does not include controls in the model nor the residual term.

each other in the scope of the entire model. This additional variable changed my model equation to $Y = x_1 + x_2 + (x_1 * x_2) + b$. The variable x_2 is the second factor, and the component $(x_1 * x_2)$ shows how the variables interact when combined. If the interaction term in this model is statistically significant, this suggests that the pre-existing sentiment of consumer confidence may help predict just how much a detected fraud will impact the economy.

I tested an additional variable in this cross-sectional analysis: the size of the loss shareholders experienced due to the fraud. I used the change in the company's market capitalization from before versus after the detection, and if this change surpassed a threshold to be considered a "big" loss, an additional interaction variable was added into the equation. I defined this threshold as the median value of loss market capitalization for fraud firms, and any observation greater than this median was classified as a big fraud. Theoretically, the size of the loss may directly and indirectly impact the effect of the detection on GDP or unemployment. The direct impact is seen most obviously in direct loss to shareholders and company employees, while more indirect effects may linger over time in the form of lost consumer confidence and related-industry losses.

The treatment of this variable is different from consumer sentiment because the existence of a big loss is dependent on a fraud being detected in the first place. Instead of adding in a second factor, this equation only added the interaction component to the otherwise simple linear regression. The resulting equation took the form $Y = x_1 + (x_1 * x_2)$, where the interaction variable showed how the existence of a massive loss impacts the detection's effect on GDP or unemployment.

While the intricacies of the model and the analysis may make this research appear complicated, these equations served to answer a few simple questions for my research. First, does fraud detection have a significant effect on economic conditions? Next, how does pre-existing sentiment effect the severity of a detection's impact on economic conditions? Lastly, does a massive loss from fraud detection impact economic conditions differently than smaller losses? The statistical research I performed through SAS helped provide some clarity to these questions.

Chapter 3: Literature Review

Precise language is integral to the field of accounting, as incorrectly defining terms like “fraud” and “material misstatement” can dramatically impact the data collected for research. Amiram, et al.’s “Financial Reporting Fraud and Other Forms of Misconduct: A Multidisciplinary Review of the Literature” (2017) provides a broad basis for these definitions and guides language of the field to a more precise consensus. The work covers far more content than will be explored in this thesis and is generally a foundational reiteration of existing concepts rather than a source for innovation. However, the fifth and final segment of the article entitled “Direction for future research on financial reporting misconduct” poses ten opportunities for future exploration in the field. One of these questions concerns the relation between macroeconomic conditions and financial reporting misconduct, the focus of my research. They claim that the central question of my research has yet to be answered in published works, and argue that if this model can be created, it could provide an avenue for economists to accomplish the tricky task of predicting downturns in real time (Amiram, et al. 2017).

Amiram, et al. cite “Booms, busts, and fraud” (2007) by Povel, Sing, and Winton as the flagship research into the relationship between financial reporting misconduct and macroeconomic conditions. In this theoretical work, Povel, et al. focus on incentives of both financial statement consumers and upper management. Consumers are incentivized to review financial statements more scrupulously during less prosperous times because the success of the company they choose to invest in is more crucial to their overall financial health. As conditions improve, however, consumers check the financials with less intensity because they assume that if the company and industry have been profitable in the past they will continue to do so in the future. While consumer's intensity of reviewing financial statements decreases, managers' risks of being caught for fraudulent misstatements decreases. They are thereby incentivized to commit fraud to better the appearance of their performance, especially as an economic peak hits and slowly begins to decline (Povel, et al. 2007). This research helps illustrate a potential positive relationship between economic conditions and the *occurrence* of financial reporting misconduct. In contrast, my analysis serves to examine whether the *revelation* of fraud helps explain future economic conditions.

In his 2004 work "Managerial Incentives, Misreporting, and the Timing of Social Learning: A Theory of Slow Booms and Rapid Recessions," Hertzberg explores the same relationship as the study above but focuses on different incentives of managers. He focuses on short-term versus long-term incentives of managers and theorizes that during times of economic prosperity, managers are more likely to manipulate profits to cover up weak performance if they are incentivized for their short-term performance. This delays the release of information about the true state of the economy to consumers, as they remain unaware of disparities between a company's actual performance and that which is publicized. Conversely, during a downturn, managers' actions are guided by long-term incentives, making them less likely to commit fraud in the present. This provides immediate information delivery to consumers (Hertzberg 2004). The combination of this work and that of Povel, et al. suggests that there could be correlation between economic conditions and financial reporting misconduct.

A member of the Povel, et al. study, Winton, also researched on another crucial work's team. The 2010 work of Wang, Winton, and Yu entitled "Corporate fraud and business conditions: Evidence from IPOs" explores a similar relationship to that of Povel, et al., while focusing exclusively on initial public offerings (IPOs). An IPO is a company's first offering of shares of their company to individuals outside of the organization. The success of this initial sale can be a primary indicator of the company's success and growth into the future and can be an especially important measure to venture capitalists who may wish to invest in the firm. Therefore, the IPO of any company is a prime time for managers to exaggerate earnings, and this research indicated that this becomes even more likely when investors perceive the economy as growing (Wang, et al. 2010). With that said, this study does not examine the impact that these frauds have on the economy.

Chapter 4: Results and Analysis

Descriptive Statistics

The purpose of running descriptive statistics prior to proceeding to regression analysis is to ensure there are no major outlying values or any other issues with the data that would interfere with accurate analysis. I conducted a basic descriptive statistics analysis of the data to safeguard against these issues.

Table 1						
Parameter	**N**	**Mean**	**Std Dev**	**Min**	**Median**	**Max**
$Unemployment_t$	130	6.502	1.711	3.947	6.004	10.906
% Change $Unemployment_t$	129	0.001	0.047	-0.094	-0.009	0.167
Count of Frauds in $Quarter_t$	130	6.938	5.158	0	6	26
Consumer $Sentiment_t$	130	86.212	12.893	54.4	90.6	110.1
$ Change GDP_t	129	103.585	72.373	-275.6	102.128	271.617
% Change GDP_t	129	0.013	0.008	-0.019	0.013	0.044
Count of Big $Frauds_t$	129	2.115	2.71	0	1	14

Table 1: Descriptive statistics, SAS output

This table summarizes the SAS output for descriptive statistics of variables used in this analysis. See Appendix A for full SAS report.

The above statistics suggested that the variables listed would be acceptable to proceed with further regression analysis.

Main Regressions

GDP as a Function of Counted Frauds

My first analysis constituted a simple regression of the change in United States GDP against the number of frauds revealed during the prior quarter. SAS analysis showed the following statistical relation between the variables.

Table 2		
	$ Change GDP_t	
Parameter	**Estimate**	**t Stat.**
Intercept	50.1222145	3.54
Count of Frauds in $Quarter_{t-1}$	0.0061996	.01
$ Change GDP_{t-1}	0.5240902	6.81
Adj. R^2	.2667	-
N	128	-

Table 2: GDP as a function of counted frauds, SAS output.

This table summarizes the SAS output for the listed variables, including an estimate for each and their associated t-values at 127 degrees of freedom. *$ Change GDP* in $ billions. See Appendix B for full SAS report.

In analyzing the results of the SAS output, I considered a t-stat greater than 1.96 statistically significant for the purposes of my research. As shown above, the count of frauds did not prove to be a statistically significant predictor of the dollar change in GDP. To further hone in on the accuracy of fraud count as a predictor of GDP, I also computed a SAS report for the number of frauds as a predictor of the percent increase in

GDP. These results depict how the number of frauds could potentially slow the growth of GDP.

Table 3		
	% Change GDP_t	
Parameter	**Estimate**	**t Stat.**
Intercept	0.0074299	4.16
Count of Frauds in $Quarter_{t-1}$	-0.0001128	-0.94
% Change GDP_{t-1}	0.5126964	4.46
Adj. R^2	.2589	-
N	128	-

Table 3: Percent change in GDP as a function of counted frauds, SAS output.

This table summarizes the SAS output for 127 degrees of freedom. See Appendix C for full SAS report.

This alternative application of the same GDP data reveals a negative association between the number of frauds and the growth of GDP, which aligns with my expectations of the market following discovered financial reporting misconduct. However, this correlation is not statistically significant.

Unemployment as a Function of Counted Frauds

This regression analysis followed a similar format to that described above for GDP, except with the national unemployment rate and the change in unemployment rate used as the dependent variables for each separate test. Once again, the a lead-lag design was used, with the dependent variable being measured in quarter t and the independent variable of interest being measure in quarter t-1.

Table 4		
	Unemployment$_t$	
Parameter	**Estimate**	**t Stat.**
Intercept	0.216093	1.28
Count of Frauds in Quarter$_{t-1}$	-0.0065056	-0.87
Unemployment$_{t-1}$	0.9759715	43.77
Adj. R^2	.9608	-
N	129	-

Table 4: Unemployment as a function of count of frauds, SAS output.

This table summarizes the SAS output for 128 degrees of freedom. See Appendix D for full SAS report.

As the estimated coefficient on count of frauds is statistically insignificant, this suggests that the number of frauds in a quarter does not help explain a change in unemployment in the following quarter. I also ran this data using the percent change in unemployment, as shown below.

Table 5		
	% Change Unemployment$_t$	
Parameter	**Estimate**	**t Stat.**
Intercept	-0.0017637	-0.31
Count of Frauds in Quarter$_{t-1}$	0.00014	0.19
% Change Unemployment$_{t-1}$	0.6140813	7.79
Adj. R^2	.3955	-
N	128	-

Table 5: Change in unemployment as a function of count of frauds, SAS output.

This table summarizes the SAS output for 128 degrees of freedom. See Appendix E for full SAS report.

Although still statistically insignificant, this specification showed a positive correlation between the number of frauds detected in a quarter and the unemployment rate.

Cross-Sectional Analysis

Consumer Sentiment

This additional variable depicts the effect of pre-existing consumer sentiment on unemployment and GDP. "Bad" consumer sentiment was identified for all observations below the median over the relevant quarters; these observations were used as a dummy variable in this analysis. While this variable did not prove statistically significant in predicting any dependent variable, the results are worth noting below.

Table 6				
	$ Change GDP$_t$		**% Change GDP$_t$**	
	Estimate	**t Stat.**	**Estimate**	**t Stat.**
Count of Frauds$_{t-1}$	.4626945	0.28	-0.0002372	-1.38
Bad Sentiment Dummy	4.0817342	.22	-0.0021954	-0.89
Frauds $_{t-1}$ * Bad Sentiment	-0.6735495	-0.31	0.000164	0.72
$ Change GDP$_{t-1}$	0.5192099	6.34	-	-
% Change GDP$_{t-1}$	-	-	0.12700396	3.9

Adj. R^2	.2553	-	.2526	-
N	128	-	128	

Table 6: Cross-sectional analysis of GDP and GDP growth as a function of count of frauds with consumer sentiment dummy variable, SAS output.

This table summarizes the separate SAS outputs for dependent variables $ Change GDP and % Change GDP, respectively. Both are measured as a function of number of frauds with a consumer sentiment dummy variable for 127 degrees of freedom. See Appendices F and G for full SAS reports.

As demonstrated above through the use of a dummy variable, pre-existing negative consumer sentiment does not have a statistically significant impact on predicting GDP or GDP growth. It also does not influence the relation between revealed frauds and GDP.

I also analyzed the cross-sectional effect of consumer sentiment as a predictor of unemployment.

Table 7				
	Unemployment$_t$		**% Change Unemployment$_t$**	
	Estimate	**t Stat.**	**Estimate**	**t Stat.**
Count of Frauds$_{t-1}$	-0.0005986	1.78	0.00108871	0.67
Bad Sentiment Dummy	0.3865785	-0.11	0.01164346	1.17
Frauds$_{t-1}$ * Bad Sentiment	-0.0106047	3.92	0.00147439	-0.48
Unemployment$_{t-1}$	0.936625	-1.09	-	-

% Change Unemployment$_{t-1}$	-	-	0.08019134	7.19
Adj. R^2	.9673	-	.3945	
N	129	-	128	

Table 7: Cross-sectional analysis of unemployment and change unemployment as a function of count of frauds with consumer sentiment dummy variable, SAS output.

This table summarizes the separate SAS outputs for dependent variables Unemployment and Unemployment % Change, respectively. Both are measured as a function of number of frauds with a consumer sentiment dummy variable for 128 and 127 degrees of freedom, respectively. See Appendices H and I for full SAS reports.

Consumer sentiment did not produce a t-value that would suggest that it is a statistically significant predictor of unemployment or percent change in unemployment. However, in the specification with unemployment as the dependent variable, it appears that unemployment tends to be lower when frauds were revealed during periods of bad sentiment.

Size of Fraud

The magnitude of fraud was determined by the loss in market capitalization from before versus after the fraud was discovered. Any fraud with lost market capitalization above the median was determined a "big" fraud. The count of these big frauds per quarter was added as a variable into the regression equation to try to achieve a model with a better fit to describe the data.

Table 8				
	$ **Change GDP$_t$**		**% Change GDP$_t$**	
	Estimate	**t Stat.**	**Estimate**	**t Stat.**

Count of $Frauds_{t-1}$	-3.3248515	-2.46	-0.0001357	-0.71
Count of Big $Frauds_{t-1}$	8.3004449	3.38	.0000561	0.18
$ Change GDP_{t-1}	0.4936099	6.01	-	-
% Change GDP_{t-1}	-	-	0.12060763	4.27
Adj. R^2	.3004	-	.253	
N	128	-	128	-

Table 8: Cross-sectional analysis of GDP and GDP growth as a function of count of frauds and count of big frauds, SAS output.

This table summarizes the separate SAS outputs for dependent variables $ Change GDP and % Change GDP, respectively. Both are measured as a function of number of frauds and number of big frauds for 127 degrees of freedom. See Appendices J and K for full SAS reports.

This data produced counterintuitive results. While the count of frauds showed a statistically significant negative correlation with the dollar change in GDP, the count of big frauds was a statistically significant positive predictor for this variable. Using percent change in GDP as the dependent variable yielded an equally perplexing output. In this case, the count of frauds in a quarter was shown to be a statistically significant positive predictor for future GDP. These results prompted an additional question for my research: why would big frauds have a positive effect on GDP, or what other factors could be at play to misconstrue the data? I explore this question further in the Correlations portion later in this paper.

I applied these same measures of market capitalization to unemployment and change in unemployment. Neither were correlated to a statistically significant degree to the occurrence of big fraud.

Table 9				
	Unemployment_t		**% Change Unemployment_t**	
	Estimate	**t Stat.**	**Estimate**	**t Stat.**
Count of Frauds_{t-1}	-0.0175874	-2.25	-0.0003129	-0.34
Count of Big Frauds_{t-1}	0.0291851	1.86	0.0011069	0.6
$\text{Unemployment}_{t-1}$	0.9816293	42.74	-	-
% Change $\text{Unemployment}_{t-1}$	-	-	0.6071031	7.63
Adj. R^2	0.9613	-	0.3924	-
N	129	-	128	-

Table 9: Cross-sectional analysis of unemployment and change in unemployment as a function of count of frauds and count of big frauds, SAS output.

This table summarizes the separate SAS outputs for dependent variables Unemployment and Unemployment % Change, respectively. Both are measured as a function of number of frauds and number of big frauds for 128 and 127 degrees of freedom, respectively. See Appendices L and M for full SAS reports.

Big Frauds Exclusively

As a final auxiliary assessment, I analyzed a simple regression between only the count of instances of big fraud and GDP.

Table 10				
	\$ Change GDP_t		**% Change GDP_t**	
	Estimate	**t Stat.**	**Estimate**	**t Stat.**
Count of Big Frauds_{t-1}	3.4484821	1.88	-0.000144	-0.73

\$ Change GDP_{t-1}	0.4967164	6.35	-	-
% Change GDP_{t-1}	-	-	0.5070854	4.4
Adj. R^2	0.2831	-	0.2561	-
N	128	-	128	-

Table 10: GDP and GDP growth as a function of count of big frauds, SAS output

This table summarizes the SAS output for \$ Change GDP and % Change GDP for 127 degrees of freedom. See Appendices N and O for full SAS reports.

Number of big frauds in a given quarter did not prove a statistically significant predictor of GDP or GDP growth.

I also computed a simple linear regression with unemployment and change in unemployment as a function of the count of big fraud in a quarter.

Table 11				
	$Unemployment_t$		**% Change $Unemployment_t$**	
	Estimate	**t Stat.**	**Estimate**	**t Stat.**
Count of Big $Frauds_{t-1}$	0.00520981	.39	0.0006464	.45
$Unemployment_{t-1}$	.98803744	42.19	-	-
% Change $Unemployment_{t-1}$	-	-	0.6100135	7.71
Adj. R^2	.9605	-	.3967	-
N	129	-	128	-

Table 11: Unemployment and change in unemployment as a function of count of big frauds, SAS output

This table summarizes the SAS output for Unemployment and Unemployment % Change for 127 degrees of freedom. See Appendices P and Q for full SAS reports.

Based on the above analysis, count of big frauds is not a statistically significant predictor of unemployment or change in unemployment.

Chapter 5: Conclusion

The fallout from the Great Recession in the United States has not been forgotten, even more than 10 years after the downturn began. While the financial and economic implications became apparent early on, research on the effects on individual American households has been trickling out in the years following. The Great Recession impacted far more than financial health; impacts reached into psychological and physical health detriments as well (Yilmazer, et al. 2015). Arguably the most alarming factor in this recession was the inaccuracy of business economists in predicting it. Most business economists produced pessimistic predictions for conditions in the year 2007, but very few if any predicted a recession of such devastating scope (Lundquist and Stekler 2012). If even our most seasoned economic specialists cannot predict a recession, how can the average citizen even begin to prepare for a downturn?

In preparing this work, I compiled literary and statistical works in order to address the dilemma above. Inherently, there are significant limitations to characterizing the economy of a nation using single numerical variables. However, the void in the research on this particular topic and the potential applicability across disciplines more than warranted its exploration. It is important to note, however, the limitations associated with this variety of research and my experimental design in particular.

First, as the data used in this study comes from the US, any conclusions drawn from this study may not necessarily generalize to other countries. While this hypothesis may be explored in other nations through future research, this is outside the scope of what I aimed to accomplish for my thesis project. Second, using a quarterly period means that I was only able to test 130 data points in coming to my conclusions. While this ensured that there was a sufficient time frame for differences to be detected between the two variables, it also meant that the bar for statistical significance would be much higher than in a larger sample. Even if there is an underlying relationship between these variables, it is possible that the model used was not be able to detect it.

Lastly, as discussed earlier, it can be difficult to ascertain with absolute confidence that the detection of financial reporting misconduct is the factor driving any changes in economic conditions. While I mitigated this by incorporating lagged versions of my dependent variables as controls, it is unlikely that I will be able to rule out all other factors as independent variables. This problem is inherent with researching something as broad and intricate as the economy of a nation, but I still firmly believe that any research that can help explain what factors play a role in downturns can be useful to consumers, economists, and future researchers.

This model presents a worthwhile pursuit for future research as it has the potential to provide a powerful tool to the arsenal of business economists. More expansive research and data collection techniques could yield results that better reflect the actual relationship, if any exists, between financial reporting misconduct and macroeconomic conditions. As government agencies become more adept at detecting corporate accounting fraud, future analysis may be better able to compile this information and provide greater insight into the nature of its effect on the economy. Though there is always a potential for discovery of a possible downturn to spiral into a self-fulfilling prophecy of a recession, if handled properly this information could be provided to government agents ahead of the peak so that they might take proactive measures to mitigate the effects of a downturn.

What's more, substantial interest in this issue could have indirect implications for financial statement consumers as well. Widely publicizing the relationship between fraud and economic conditions may encourage users to check financial statements more intensely, inadvertently creating a checking system on firms without any government expenditure. This could potentially decrease instances of corporate fraud overall and would help keep firms accountable for their responsibility to provide accurate information to consumers.

Appendices

Appendix A

The SAS System

The MEANS Procedure

Variable	Label	N	Mean	Std Dev	Minimum	Median	Maximum
Q_	Q#	130	65.5	37.672	1	65.5	130
observation_date	observation_date	130	13194.254	3439.885	7305	13194.5	19084
Unemployment____	Unemployment (%)	130	6.502	1.711	3.947	6.004	10.906
Unemployment__Decimal_	Unemployment (Decimal)	130	0.065	0.017	0.039	0.06	0.109
Unemployment__Change_	Unemployment (Change)	129	0.001	0.047	-0.094	-0.009	0.167
Count_of_Frauds_in_Quarter	Count of Frauds in Quarter	130	6.938	5.158	0	6	26
Change_in_Count_of_Frauds_in_Qua	Change in Count of Frauds in Quarter	129	0	5.184	-15	0	16
__Change_in_Count_in_Frauds_in_Q	% Change in Count in Frauds in Quarter	119	-0.371	1.54	-9	0	1
Sentiment	Sentiment	130	86.212	12.893	54.4	90.6	110.1
Bad_Sentiment_Dummy__1_0_	Bad Sentiment Dummy (1/0)	130	0.5	0.502	0	0.5	1
GDP____billions_	GDP ($ billions)	130	8676.554	4059.872	2789.842	7950.654	16152.257
Change_in_GDP____billions_	Change in GDP ($ billions)	129	103.585	72.373	-275.644	102.128	271.617
__Change_in_GDP	% Change in GDP	129	0.013	0.008	-0.019	0.013	0.044
__Change_in___Growth	% Change in % Growth	128	0	0.008	-0.032	0	0.023
Count_of_Big_Frauds	Count of Big Frauds	130	2.115	2.71	0	1	14
Change_in_Big_Frauds	Change in Big Frauds	129	0	2.669	-10	0	11
F1Unemployment	Unemployment (%)	129	6.503	1.717	3.947	5.954	10.906
F1Unemployment_Decimal	Unemployment (Decimal)	129	0.065	0.017	0.039	0.06	0.109
F1Unemployment_Change	Unemployment (Change)	129	0.001	0.047	-0.094	-0.009	0.167
F1GDP_billions	GDP ($ billions)	129	8722.188	4042.091	2797.352	8032.84	16152.257
F1Change_in_GDP_billions	Change in GDP ($ billions)	129	103.585	72.373	-275.644	102.128	271.617
F1Change_in_GDP	% Change in GDP	129	0.013	0.008	-0.019	0.013	0.044
F1_Change_in_Growth	% Change in % Growth	128	0	0.008	-0.032	0	0.023

Appendix B

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP_billions

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP_billions	104.3352
Sum of F1Change_in_GDP_billions	13354.9

Fit Statistics	
R-square	0.2783
Adjusted R-square	0.2667
Root MSE	61.7854
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	24.44	<.0001
Intercept	1	12.54	0.0006
Count_of_Frauds_in_Quarter	1	0	0.9952
Change_in_GDP____billions_	1	46.35	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	50.1222145	14.1520637	3.54	0.0006
Count_of_Frauds_in_Quarter	0.0061996	1.0298425	0.01	0.9952
Change_in_GDP____billions_	0.5240902	0.0769844	6.81	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix C

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP	0.01357
Sum of F1Change_in_GDP	1.73708

Fit Statistics	
R-square	0.2705
Adjusted R-square	0.2589
Root MSE	0.007075
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	9.96	<.0001
Intercept	1	17.3	<.0001
Count_of_Frauds_in_Quarter	1	0.89	0.3466
__Change_in_GDP	1	19.88	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0074299	0.00178656	4.16	<.0001
Count_of_Frauds_in_Quarter	-0.0001128	0.00011936	-0.94	0.3466
__Change_in_GDP	0.5126964	0.11498583	4.46	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix D

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment

Data Summary	
Number of Observations	129
Mean of F1Unemployment	6.5033
Sum of F1Unemployment	838.92633

Fit Statistics	
R-square	0.9614
Adjusted R-square	0.9608
Root MSE	0.3402
Denominator DF	128

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	1238.73	<.0001
Intercept	1	1.65	0.2013
Count_of_Frauds_in_Quarter	1	0.75	0.3869
Unemployment____	1	1916.23	<.0001

Note: The denominator degrees of freedom for the F tests is 128.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.216093	0.16823872	1.28	0.2013
Count_of_Frauds_in_Quarter	-0.0065056	0.00749386	-0.87	0.3869
Unemployment____	0.9759715	0.02229532	43.77	<.0001

Note: The denominator degrees of freedom for the t tests is 128.

Appendix E

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment_Change

Data Summary	
Number of Observations	128
Mean of F1Unemployment_Change	-0.0001814
Sum of F1Unemployment_Change	-0.02321

Fit Statistics	
R-square	0.405
Adjusted R-square	0.3955
Root MSE	0.03513
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	30.34	<.0001
Intercept	1	0.09	0.7586
Count_of_Frauds_in_Quarter	1	0.04	0.8491
Unemployment__Change_	1	60.65	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0017637	0.00572609	-0.31	0.7586
Count_of_Frauds_in_Quarter	0.00014	0.00073448	0.19	0.8491
Unemployment__Change_	0.6140813	0.07885229	7.79	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix F

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP_billions

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP_billions	104.3352
Sum of F1Change_in_GDP_billions	13354.9

Fit Statistics	
R-square	0.2788
Adjusted R-square	0.2553
Root MSE	62.2642
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	4	12.32	<.0001
Intercept	1	14.87	0.0002
Count_of_Frauds_in_Quarter	1	0.08	0.7772
Bad_Sentiment_Dummy__1_0_	1	0.05	0.8291
Frauds_x_BadSentiment	1	0.09	0.7601
Change_in_GDP____billions_	1	40.17	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	47.5056342	12.3205268	3.86	0.0002
Count_of_Frauds_in_Quarter	0.4626945	1.631333	0.28	0.7772
Bad_Sentiment_Dummy__1_0_	4.0817342	18.8739787	0.22	0.8291
Frauds_x_BadSentiment	-0.6735495	2.2010594	-0.31	0.7601
Change_in_GDP____billions_	0.5192099	0.0819156	6.34	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix G

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP	0.01357
Sum of F1Change_in_GDP	1.73708

Fit Statistics	
R-square	0.2761
Adjusted R-square	0.2526
Root MSE	0.007105
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	4	8.43	<.0001
Intercept	1	13.33	0.0004
Count_of_Frauds_in_Quarter	1	1.92	0.1686
Bad_Sentiment_Dummy__1_0_	1	0.8	0.374
Frauds_x_BadSentiment	1	0.52	0.4702
__Change_in_GDP	1	15.19	0.0002

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0091151	0.00249656	3.65	0.0004
Count_of_Frauds_in_Quarter	-0.0002372	0.00017131	-1.38	0.1686
Bad_Sentiment_Dummy__1_0_	-0.0021954	0.00246053	-0.89	0.374
Frauds_x_BadSentiment	0.000164	0.00022644	0.72	0.4702
__Change_in_GDP	0.4949343	0.12700396	3.9	0.0002

Note: The denominator degrees of freedom for the t tests is 127.

Appendix H

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment

Data Summary	
Number of Observations	129
Mean of F1Unemployment	6.5033
Sum of F1Unemployment	838.92633

Fit Statistics	
R-square	0.9684
Adjusted R-square	0.9673
Root MSE	0.3104
Denominator DF	128

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	4	884.31	<.0001
Intercept	1	3.17	0.0773
Count_of_Frauds_in_Quarter	1	0.01	0.9129
Bad_Sentiment_Dummy__1_0_	1	15.36	0.0001
Frauds_x_BadSentiment	1	1.18	0.2797
Unemployment____	1	1732.95	<.0001

Note: The denominator degrees of freedom for the F tests is 128.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.2711853	0.15225927	1.78	0.0773
Count_of_Frauds_in_Quarter	-0.0005986	0.00546316	-0.11	0.9129
Bad_Sentiment_Dummy__1_0_	0.3865785	0.09862298	3.92	0.0001
Frauds_x_BadSentiment	-0.0106047	0.0097676	-1.09	0.2797
Unemployment____	0.936625	0.02249947	41.63	<.0001

Note: The denominator degrees of freedom for the t tests is 128.

Appendix I

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment_Change

Data Summary	
Number of Observations	128
Mean of F1Unemployment_Change	-0.0001814
Sum of F1Unemployment_Change	-0.02321

Fit Statistics	
R-square	0.4135
Adjusted R-square	0.3945
Root MSE	0.03516
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	4	15.84	<.0001
Intercept	1	1.34	0.2484
Count_of_Frauds_in_Quarter	1	0.45	0.5056
Bad_Sentiment_Dummy__1_0_	1	1.36	0.2454
Frauds_x_BadSentiment	1	0.23	0.6356
Unemployment__Change_	1	51.64	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0103619	0.00893645	-1.16	0.2484
Count_of_Frauds_in_Quarter	0.0007269	0.00108871	0.67	0.5056
Bad_Sentiment_Dummy__1_0_	0.013589	0.01164346	1.17	0.2454
Frauds_x_BadSentiment	-0.0007004	0.00147439	-0.48	0.6356
Unemployment__Change_	0.5762438	0.08019134	7.19	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix J

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP_billions

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP_billions	104.3352
Sum of F1Change_in_GDP_billions	13354.9

Fit Statistics	
R-square	0.3169
Adjusted R-square	0.3004
Root MSE	60.3488
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	3	18.46	<.0001
Intercept	1	16.18	<.0001
Count_of_Frauds_in_Quarter	1	6.06	0.0152
Count_of_Big_Frauds	1	11.41	0.001
Change_in_GDP____billions_	1	36.15	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	58.9131363	14.6454765	4.02	<.0001
Count_of_Frauds_in_Quarter	-3.3248515	1.3507231	-2.46	0.0152
Count_of_Big_Frauds	8.3004449	2.4572651	3.38	0.001
Change_in_GDP____billions_	0.4936099	0.0820989	6.01	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix K

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP	0.01357
Sum of F1Change_in_GDP	1.73708

Fit Statistics	
R-square	0.2707
Adjusted R-square	0.253
Root MSE	0.007102
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	3	7.47	0.0001
Intercept	1	17.54	<.0001
Count_of_Frauds_in_Quarter	1	0.51	0.4781
Count_of_Big_Frauds	1	0.03	0.858
__Change_in_GDP	1	18.22	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0074416	0.00177674	4.19	<.0001
Count_of_Frauds_in_Quarter	-0.0001357	0.00019074	-0.71	0.4781
Count_of_Big_Frauds	0.0000561	0.00031273	0.18	0.858
__Change_in_GDP	0.5148791	0.12060763	4.27	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix L

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment

Data Summary	
Number of Observations	129
Mean of F1Unemployment	6.5033
Sum of F1Unemployment	838.92633

Fit Statistics	
R-square	0.9622
Adjusted R-square	0.9613
Root MSE	0.3378
Denominator DF	128

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	3	878.19	<.0001
Intercept	1	1.35	0.2471
Count_of_Frauds_in_Quarter	1	5.04	0.0265
Count_of_Big_Frauds	1	3.46	0.0652
Unemployment____	1	1826.85	<.0001

Note: The denominator degrees of freedom for the F tests is 128.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.1946522	0.1674049	1.16	0.2471
Count_of_Frauds_in_Quarter	-0.0175874	0.00783344	-2.25	0.0265
Count_of_Big_Frauds	0.0291851	0.01568999	1.86	0.0652
Unemployment____	0.9816293	0.02296659	42.74	<.0001

Note: The denominator degrees of freedom for the t tests is 128.

Appendix M

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment_Change

Data Summary	
Number of Observations	128
Mean of F1Unemployment_Change	-0.0001814
Sum of F1Unemployment_Change	-0.02321

Fit Statistics	
R-square	0.4067
Adjusted R-square	0.3924
Root MSE	0.03522
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	3	20.15	<.0001
Intercept	1	0.03	0.8659
Count_of_Frauds_in_Quarter	1	0.12	0.7307
Count_of_Big_Frauds	1	0.36	0.552
Unemployment__Change_	1	58.14	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0009431	0.00557239	-0.17	0.8659
Count_of_Frauds_in_Quarter	-0.0003129	0.00090711	-0.34	0.7307
Count_of_Big_Frauds	0.0011069	0.00185603	0.6	0.552
Unemployment__Change_	0.6071031	0.07961735	7.63	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix N

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP_billions

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP_billions	104.3352
Sum of F1Change_in_GDP_billions	13354.9

Fit Statistics	
R-square	0.2944
Adjusted R-square	0.2831
Root MSE	61.0918
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	21.01	<.0001
Intercept	1	15.55	0.0001
Count_of_Big_Frauds	1	3.54	0.062
Change_in_GDP____billions_	1	40.26	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	45.5863811	11.5606854	3.94	0.0001
Count_of_Big_Frauds	3.4484821	1.8316449	1.88	0.062
Change_in_GDP____billions_	0.4967164	0.0782824	6.35	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix O

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Change_in_GDP

Data Summary	
Number of Observations	128
Mean of F1Change_in_GDP	0.01357
Sum of F1Change_in_GDP	1.73708

Fit Statistics	
R-square	0.2678
Adjusted R-square	0.2561
Root MSE	0.007088
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	10.66	<.0001
Intercept	1	15.58	0.0001
Count_of_Big_Frauds	1	0.53	0.4665
__Change_in_GDP	1	19.34	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0070206	0.00177862	3.95	0.0001
Count_of_Big_Frauds	-0.000144	0.00019719	-0.73	0.4665
__Change_in_GDP	0.5070854	0.11529964	4.4	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

Appendix P

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment

Data Summary	
Number of Observations	129
Mean of F1Unemployment	6.5033
Sum of F1Unemployment	838.92633

Fit Statistics	
R-square	0.9611
Adjusted R-square	0.9605
Root MSE	0.3413
Denominator DF	128

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	1256.36	<.0001
Intercept	1	0.26	0.6104
Count_of_Big_Frauds	1	0.15	0.6964
Unemployment____	1	1780.21	<.0001

Note: The denominator degrees of freedom for the F tests is 128.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.08120678	0.15901172	0.51	0.6104
Count_of_Big_Frauds	0.00520981	0.01332024	0.39	0.6964
Unemployment____	0.98803744	0.02341736	42.19	<.0001

Note: The denominator degrees of freedom for the t tests is 128.

Appendix Q

The SAS System

The SURVEYREG Procedure

Regression Analysis for Dependent Variable F1Unemployment_Change

Data Summary	
Number of Observations	128
Mean of F1Unemployment_Change	-0.0001814
Sum of F1Unemployment_Change	-0.02321

Fit Statistics	
R-square	0.4062
Adjusted R-square	0.3967
Root MSE	0.03509
Denominator DF	127

Tests of Model Effects

Effect	Num DF	F Value	Pr > F
Model	2	30.3	<.0001
Intercept	1	0.27	0.6031
Count_of_Big_Frauds	1	0.2	0.6524
Unemployment__Change_	1	59.5	<.0001

Note: The denominator degrees of freedom for the F tests is 127.

Estimated Regression Coefficients

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.002162	0.0041481	-0.52	0.6031
Count_of_Big_Frauds	0.0006464	0.00143197	0.45	0.6524
Unemployment__Change_	0.6100135	0.07908032	7.71	<.0001

Note: The denominator degrees of freedom for the t tests is 127.

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