Income Statement Fraud and Balance Sheet Fraud: Different Manipulations, Different Incentives

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Abstract

I find managers commit income statement fraud (fraud in which manipulations increase net income) when market price sensitivity to earnings news is high and their firms' stock price is relatively more sensitive to idiosyncratic earnings performance. Managers commit balance sheet fraud (fraud in which manipulations increase net assets but do not affect net income) when market-wide default risk is high and their firms have greater financial constraints. The results hold in samples of fraud firms derived from SEC enforcements, class action lawsuits, and a subsample in which fraud was detected internally or by employee whistleblowers.

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1. INTRODUCTION

Stakeholders provide managers with incentives to increase earnings, maintain a healthy balance sheet with strong capital and liquidity ratios, maintain the ability to access the capital markets, and have strong operating cash flows to fund current operations. Such incentives include compensation (Antle and Smith 1986) and tenure (Martin and McConnell 1991). Incentives to deliver strong performance also create incentives to manipulate financial statements (Benmelech, Kandel, and Veronesi 2010). Managers can commit financial statement fraud by intentionally misreporting any combination of individual transactions in response to these incentives.

Income statement and balance sheet information is used by numerous agents for numerous purposes. A manager can have strong incentives to improve one financial statement while having *relatively* weaker incentives to improve the other. For example, survey evidence from Graham, Harvey, and Rajgopal (2005) indicates that managers would be willing to sacrifice long term value by delaying projects or decreasing discretionary spending to meet a quarterly *earnings* target. A manager can commit income statement fraud (defined as fraud which increases net income and does not involve material manipulations unrelated to net income) in response to incentives to deliver strong earnings[1]. Conversely, if the manager wishes to issue debt to finance capital expenditures then having a strong *balance sheet* with regards to current debt obligations, the firm's debt to equity ratio, and other ratios indicative of the long run ability to service the debt could be more important than short term quarterly earnings performance. A manager can commit balance sheet fraud (defined as fraud which increases net assets but does not involve material manipulations related to net income) in response to incentives for a strong balance sheet.

[1] An example is recording fictitious revenues. Though the balance sheet is also affected by this entry (most likely by an increase in accounts receivable) the effect on the balance sheet is directly related to the manipulation of revenue.

Collectively, prior research argues fraud is a response to environmental pressures (Ball 2009) more likely to occur in firms with certain idiosyncratic characteristics, such as firms with weak corporate governance or a need to raise capital. Analytical research predicts more managers commit fraud during relatively strong economic periods[2], while empirical research finds mixed results on the relations between fraud and a firm's financial constraints, need for capital, and prior financial performance. Research has not considered that environmental pressures to commit income statement or balance sheet fraud are different and might vary independently or that different idiosyncratic characteristics are associated with income statement and balance sheet fraud.

I find more managers begin to commit income statement fraud in periods of high market price sensitivity to earnings news and that these firms' stock prices were relatively more sensitive to earnings performance. These relations have greater statistical significance than those for balance sheet fraud. Conversely, I find that more managers begin to commit balance sheet fraud in periods with higher default risk and that these firms had greater financial constraints. These relations have greater statistical significance than those for income statement fraud.

Having found evidence that managers commit income statement and balance sheet fraud in response to different environmental pressures, I then analyze how associations between fraud, regardless of type, and firm-level price sensitivity to earnings news and financial constraints vary through time. Frauds that began between 1992 and 2000 are positively and significantly associated with firms' price sensitivity to earnings news however frauds beginning prior to 1992 and after 2000 are not. 60 percent of all income statement frauds occur during this between 1992 and 2000, while only 40 percent occurs in the remaining 16 years of the sample. Conversely, only 34 percent of balance sheet frauds occur during this period. Further, the association between fraud and firms' financial constraints is positive and significant in the periods 1986-1991 and 2001-2010 but not significant from 1992 through 2000.

[2] See Hertzberg (2005), Povel, Singh, and Winton (2007), and Strobl (2013) for examples.

Given that income statement and balance sheet fraud are associated with different incentives and that the proportion of income statement and balance sheet fraud varies considerably through time, it is possible that fraud studies sampling from different time periods produce inconsistent results because the samples are significantly different. Samples from different time periods which do not take into account fraud type might not be comparable for certain research questions. To further explore this possibility, I analyze the association between fraud and board of director independence. Prior research reports mixed results on this association (Beasley (1996), Dechow, Sloan, and Sweeney (1996), Agrawal and Chadha (2005)) but the sample periods are different in these studies. I find the association is negative and significant for frauds prior to 2000 – more independence among directors is associated with a reduced likelihood of fraud. But, for frauds beginning in 2000 or later, the association is not significant and the association is actually positive[3]. These results are consistent with those reported in prior studies given the sample periods analyzed in those studies.

One limitation of fraud studies is that frauds which are never detected are omitted from the analysis. It is possible that regulators place greater emphasis on detecting certain types of fraud during certain economic periods and that this emphasis could be correlated with the macroeconomic proxies used in this study. To address this concern I re-estimate models analyzing income statement and balance sheet fraud with a sample of alleged frauds from class action lawsuits used in Dyck, Morse, and Zingales (2007) (hereafter DMZ). This sample does not suffer from biases regulators may have in detecting fraud and/or releasing enforcement actions. I then use the classification method employed by DMZ to denote who detected the frauds in my sample and repeat analyses using only frauds detected by the firm itself or by employee whistleblowers. There is little reason to think an employee whistleblower decides to blow the whistle on fraud based on whether it is related to earnings or that the decision varies with market-wide

[3] Machine readable board of director data is not available for the 1986-1991 period discussed in the previous paragraph so the relatively low prevalence of income statement fraud during those years does not have significance for this analysis.

default rates. These analyses should mitigate, though not eliminate concerns about correlated omitted variables.

This paper contributes to the literature in several ways. First, it is the first paper (of which I am aware) which documents that managers manipulate the income statement and balance sheet in response to different incentives and at different times. This highlights that all frauds are not homogenous and that researchers should consider the economic theories they are testing and how they relate to different types of manipulations when creating samples for empirical tests. Further, regulators and auditors should perhaps focus on certain types of fraud and firm-level attributes during certain periods. Second, this is the first empirical paper which documents how fraud varies with macroeconomic forces, specifically market price sensitivity to earnings news and market-wide default risk, when controlling for idiosyncratic incentives. Market forces create incentives for managers to misreport incremental to those at the firm level. Third, this is the first paper that documents how the association between fraud and firm-level determinants varies through time; researchers can find different results depending on what period the sample is drawn from. Finally, it provides a novel explanation for inconsistent results reported in the literature on the relation between financial statement fraud and board independence, opening the possibility that other prior results are dependent upon the time period from which the fraud sample is drawn.

2. HYPOTHESIS DEVELOPMENT

Prior analytical and empirical research provides evidence that both market and idiosyncratic forces create incentives for managers to commit financial statement fraud (hereafter fraud). While this research does not investigate whether different incentives are associated with income statement fraud (hereafter IS) or balance sheet fraud (hereafter BS), some proposed theories are more likely related to earnings, while others less likely.

2.1 Income Statement Fraud

Several studies find evidence that more managers commit fraud during relatively strong economic periods; much of this research is centered on earnings manipulations and maintaining strong stock price performance. When discussing reasons for the wave of corporate scandals in the late 1990s, Ball (2009) argues that high growth is built into performance expectations during a boom period and that managers therefore are pressured to deliver strong earnings growth[4]. When, inevitably, firms experience declining performance relative to their own expectations and/or their peers, the managers of these firms find themselves unable to meet their heightened expectations. Such managers have particularly strong incentives to meet earnings expectations. Survey evidence from Graham, Harvey, and Rajgopal (2005) indicates that managers manipulate earnings to maintain or increase their firm's stock price. Dechow, Ge, Larson, and Sloan (2011) find evidence that fraud firms have strong prior stock price performance. That accounting frauds happen after a sustained run of strong market performance by firms with strong prior performance is consistent with Jensen's (2005) theory of overvalued equity.

Benmelech, Kandel, and Veronesi (2010) show that while incentive-based compensation induces managers to exert costly effort, it also creates incentives to conceal bad news about future growth options. They note that fraudulent reporting is one possible response to poor performance in periods where price sensitivity to earnings news is high. The price response to earnings news is not constant through time and the incentives to report positive earnings news are stronger in periods where the price response is larger, ceteris paribus.

Collectively, prior research provides evidence that market and idiosyncratic forces can create incentives for managers to manipulate earnings but are silent about motives to manipulate the balance sheet (independent of the residual effect of the earnings manipulations). They predict more managers manipulate earnings when price sensitivity to earnings is highest. This prediction has never been tested specifically against known cases of IS fraud separate from BS fraud. The prior research provides the theoretical motivation for my first set of hypotheses:

[4] Galbraith (1961) makes a similar case for the events leading up to the 1929 market crash.

Hypothesis 1A:

Managers commit income statement fraud when market price sensitivity to earnings news is high.

Hypothesis 1B:

Firms where income statement fraud occurs have relatively high price sensitivity to earnings news.

2.2 Balance Sheet Fraud

The income statement and balance sheet are used by different agents for different purposes. For example, Watts (2003) notes the prevalence of the balance sheet's use in contracting. Common covenants written into debt contracts include restrictions against issuing more debt, requiring a minimum level of working capital, and placing limits on certain ratios such as interest coverage and debt-to-equity. When analyzing developments in credit risk management, Altman and Saunders (1997) cite the extensive use of the balance sheet in credit risk assessment. Bernanke and Gertler (1989) develop a model of the business cycle where higher net assets reduce the agency costs of financing real capital investments. In their model, the balance sheet is more important in periods of high financial distress. Many of the incentives for managers to maintain a strong balance sheet relate to financial constraints, credit risk, or bankruptcy risk and the strength of these incentives varies through time.

The need for external financing is one hypothesized determinant of fraud. Both Efendi, Srivastava, and Swanson (2007) and Richardson, Tuna, and Wu (2003) find that managers commit fraud because of a need to raise external financing, yet Beneish (1999) finds no evidence of this. One potential issue is that most prior research analyzes small samples of fraud over brief time periods. The type of frauds committed and the economic environment can differ across studies. Also, these studies do not consider the role of macroeconomic forces or whether different types of fraud are more likely related to capital constraints. It is easier for firms to raise capital, and do so on favorable terms, during strong economic periods and it is easier for firms with strong prior performance to raise capital. Therefore, firms that might otherwise be constrained by their balance sheet profile (i.e. firms with high levels of debt or firms nearing covenant violations) have less incentive to commit fraud in response to financial constraints during strong economic periods, given the relative ease of raising capital. Such firms are also less likely to have strong prior performance given their weak balance sheet. The macro and microeconomic conditions that create incentives to manipulate earnings differ from those that create incentives to improve net assets, avoid covenant violations, and ease access to external financing.

Prior research on the role of the balance sheet and on the hypothesized association between fraud and firms' financial constraints lead to my second set of hypotheses:

Hypothesis 2A:

Managers commit balance sheet fraud during periods with greater market-wide default risk.

Hypothesis 2B:

Firms where balance sheet fraud occurs have relatively severe financial constraints.

2.3 Effect of Treating Frauds as Homogenous

Prior research does not distinguish between IS and BS fraud. Most of these studies analyze small samples over brief time periods. The results of these studies are often mixed. For example, Beasley (1996) finds that fraud is decreasing in board independence while Agrawal and Chadha (2005) find no such relation. Beasley (1996) analyses frauds from 1980-1991 while Agrawal and Chadha (2005) analyze violations from 2000-2001. Dechow, Sloan, and Sweeney (1996) find a positive association between fraud and a desire for low cost financing with a sample of 92 fraud firms while Beneish (1999) finds no such evidence in a sample of 64 fraud firms. Figure 1 lists the sample sizes of 17 prior papers on financial statement manipulation. Half have fewer than 60 fraud firms and only two have more than 100 fraud firms[5]. Given that only 50 percent of frauds detected and enforced by the SEC represent earnings manipulations alone (and only 20 percent net assets alone) the inconsistent results in prior research could be caused, in part, by significantly different proportions of IS and BS fraud in the respective samples.

[5] A number of papers look at earnings restatements and have larger samples. Restatement studies often produce results inconsistent with fraud studies.

Figure 2 lists the sample periods of 15 prior studies on financial statement manipulation[6]. Of the 15 papers listed, ten have samples within the years 1996 through 2002. Further, seven of the papers have a sample period which covers five years or less.

If macro incentives associated with IS fraud are not associated with BS fraud (and vice versa) i.e. the aggregate composition of fraud type varies through time, then these studies could be analyzing significantly different samples with different fraud type compositions. Studies with larger samples over a greater number of years might fail to document associations that are significant for one type of fraud but insignificant for another type because IS and BS fraud are committed for different reasons. Broadly, treating all frauds as the same event can lead to inconsistent, inaccurate, and incomplete results. Analyzing all frauds using the same specification but over different time periods and finding different results provides evidence of the importance of incorporating fraud type into research design. It also documents the pitfalls that accompany small sample analyses over brief time periods; when the composition of the sample changes the results can change as well.

3. SAMPLE, DATA, AND SUMMARY STATISTICS

3.1 Sample and Data

I use SEC Accounting and Auditing Enforcement Releases (AAERs) as a proxy for fraud. These releases summarize investigations the SEC brings against the agents of firms for violations of SEC and federal rules. To collect my sample, I read AAERs 84 – 3638 which were released between January 15, 1986 and February 13, 2015. I only include firms for which the following can be determined: whether the firm's financial statements were materially misstated; whether the manipulation was related to the income statement or balance sheet (or both); and the year the violation began[7]. I exclude AAERs related to

[6] These papers represent a subset of fraud research and several study manipulations not deemed fraudulent. Several papers studying fraud do not specify the specific years that sample observations occur and so are not listed.
[7] The Internet Appendix includes two AAERs; one was issued for IS fraud and the other for BS fraud. These examples document the accuracy with which these three pieces of information can be collected.

income or asset understatement.[8] My hypotheses pertain to frauds where the primary motivation was to improve the current period income statement or balance sheet.

AAERs offer several advantages relative to other proxies for fraud. First, it is clear whether the managers of firms in the AAER sample actually committed fraud. I am specifically interested in violations of Section 13(a) and Section 13(b)(2)(A) of the Securities Exchange Act of 1934. AAERs provide the year (and exact date in some cases) the fraud began. Finally, over 90 percent of AAERs related to accounting fraud provide clear information regarding whether the income statement or the balance sheet was manipulated.

That said, AAERs have limitations. AAERs only document frauds that are detected[9] and ultimately enforced. This is a potential concern if detection and enforcement of IS and BS fraud vary independently through time. However, this would change the nature of the detection/enforcement environments several years (in most cases) after the fraud began so it is not clear how this would influence market conditions or firm-level incentives when the fraud began. If the SEC begins to place increased emphasis on income related fraud in 2003, that cannot influence whether the frauds they detect began in 2000, 2001, or any other year. Still, to address this concern I analyze two additional samples of fraud firms.

First, I use a sample of alleged frauds from class action lawsuits used in DMZ. This sample is unrelated to regulators' enforcement decisions and therefore will not suffer from such potential bias in the AAER sample. There is little reason reason to expect the decision to bring a class action lawsuit will be related to the state of the economy or firm-level incentives which were in place several years before the lawsuit was even filed. Further, there is no evidence that the decision to bring a class action lawsuit should vary with whether the fraud was related to the income statement or balance sheet and in a way

[8] There are 5 AAER firms with frauds related to earnings/asset understatement with all required data. This could be because fewer managers have incentives to commit this type of fraud or because the SEC has weaker incentives to prosecute such violations.

[9] This is true for all ex post measures of fraud.

correlated with the macro and micro incentives I analyze in this study, particularly given that these lawsuits are often filed well before detailed evidence of fraud is even discovered. Where possible, I classify their sample as IS or BS fraud using the same process used for AAERs. Some class action lawsuits are clearly unrelated to financial statement fraud and are excluded from the analysis[10]. After removing cases unrelated to fraud I am left with a sample of 90 cases from 1995-2003.

Second, I analyze a sample of AAER firms for which the fraud was detected by management or employee whistleblowers. DMZ note that regulators rarely detect fraud themselves. There is little reason to think a whistleblower's decision to come forward varies inter-temporally on whether the fraud was related to the income statement or balance sheet. Following the process employed in DMZ, I categorize the initial source of information related to the fraud and note whether this source is part of the management of the firm or an employee whistleblower. DMZ find that 104 out of 230 (45%) cases are first brought to light by internal governance or employee whistleblowers. In my sample I find that 50% of IS and BS frauds are first detected by internal governance or employee whistleblowers.

Another concern related to AAERs is whether they accurately categorize IS and BS fraud. Some AAERs provide great detail regarding the specific accounts and dollar amounts manipulated and the exact dates manipulations took place, while many others do not approach this level of detail. Categorization based on the exact accounts and amounts manipulated is quite difficult but nearly every AAER (over 90 percent) provides enough information to determine whether net income was manipulated and whether manipulations unrelated to net income took place. Further, while the SEC may place emphasis on certain types of fraud during certain periods, there is little reason to think it would be so negligent in its investigation to fail to detect material income manipulations in periods when it is more concerned about balance sheet manipulations or that it would choose not to disclose significant manipulations in the AAER. Therefore, the categorization of fraud type employed in this study should not suffer from noise or

[10] For example, Service Corporation International faced a class action lawsuit due to desecration of gravesites and for leaving dug up corpses in the woods.

bias due to variation in the level of detail provided in AAERs. Results using the DMZ sample should also reduce concerns about categorization of fraud type that are unique to AAERs, but potentially have their own categorization concerns. I exclude the firm from my analyses in cases of ambiguity. Table 1 documents the composition of the samples used to test my hypotheses. Of the 459 frauds with CRSP/Compustat identifiers about half are IS frauds and about 20 percent are BS frauds (with 30 percent affecting both financial statements through independent manipulations).

I distinguish failure years (the first year fraud began) using these indicator variables: *IS* equals one the first year income statement fraud begins; zero otherwise. *BS* equals one the first year balance sheet fraud begins; zero otherwise. *FRAUD* equals one the first year fraud of any kind begins; zero otherwise.

I calculate *PE MKT*, the value weighted annual market price-earnings ratio as a proxy for market price sensitivity to earnings news[11]. The objective is to succinctly capture how sensitive the market was to earnings over the course of the year. I also estimate a firm-specific price sensitivity to earnings measure, *EARN SEN*, computed as the annual percentile rank of the firm's price-earnings ratio[12]:

I calculate *DEFAULT RISK* as the difference between the long-term BAA corporate bond rate and the 10 year Treasury bill rate to proxy for market-wide annual default risk[13]. Prior research uses

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[11] Results hold when calculating an equal weighted price-earnings ratio. Value weighting should reduce concerns about the measure being unduly influenced by smaller firms with large variances in earnings sensitivity. Nevertheless, I re-estimate models calculating *PE MKT* excluding firms with less than $100 million in market capitalization and find the results hold.

[12] I use the percentile rank to address problems arising from negative price-earnings ratios. Negative PE ratios have no interpretive value and also create a computational problem because when holding price constant firms with small losses have more negative (lower) PE ratios than firms with large losses. When earnings are positive the opposite is true. I correct for this when calculating the percentile rank. Additionally, I use price scaled by sales as an alternative proxy and use the firm's actual PE ratio and exclude firms with losses and find that the results are unchanged.

[13] In robustness analysis I employ a separate measure to consider credit supply in the economy. Specifically, *TIGHTNESS* uses the Federal Reserve Board's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices and takes a value of 1 in years where tightness is in the top quartile of the distribution; 0 otherwise (Bushman, Williams, and Wittenberg-Moerman 2015). This measure is not available until the second quarter of 1990 and therefore cannot be used for the first 5 years of the sample. Given the similarity in results using both measures, I report results using *DEFAULT RISK* to maximize the sample size.

various measures for firm-specific financial constraints and/or need for capital. I use the measure developed by Kaplan and Zingales (1997) which is shown in numerous settings to consistently capture overall financial constraints[14]. Following Baker, Stein, and Wurgler (2003) I construct the five variable KZ financial constraint measure for each firm/year as the following linear combination:

$$KZ_{i,t} = -\frac{1.002CF_{i,t}}{A_{i,t-1}} - \frac{39.368D_{i,t}}{A_{i,t-1}} - \frac{1.315C_{i,t}}{A_{i,t-1}} + 3.139B_{i,t} + 0.283Q_{i,t}, \tag{1}$$

where $CF_{it}/A_{i,t-1}$ is cash flow over prior year (t-1) assets; $D_{i,t}/A_{i,t-1}$ is cash dividends over prior year assets; $C_{i,t}/A_{i,t-1}$ is cash balances over prior year assets; $B_{i,t}$ is total debt divided by the sum of total debt and book equity measured at year-end, and Tobin's Q ($Q_{i,t}$) is the market value of equity (price times shares outstanding) plus assets minus the book value of equity, all divided by assets.

3.2 Summary Statistics

Table 2, Panel A describes the macro variables and micro variables for fraud firms and non-fraud firms[15]. Fraud firms differ significantly from non-fraud firms on potentially important dimensions. Fraud firms have greater earnings sensitivity (*EARN SEN)*, are more financially constrained (*KZ*), have larger abnormal returns (*AB RET)*, are larger (*SIZE)*, have a higher return on assets (*ROA)*, and are more likely to have a recent initial public offering (*IPO*). The statistics suggest that fraud firms are either quite large (based on size) or quite young (based on IPOs). IS and BS fraud firm characteristics also differ. Table 2, Panel A documents that IS fraud firms have greater earnings sensitivity, are less financially constrained, have larger abnormal returns, are smaller (significant at the median only), have a higher return on assets, and are more likely to have a recent IPO. These differences are consistent with the notion that managers of IS and BS fraud firms commit fraud under different conditions and circumstances. All continuous firm-level variables are winsorized at the 0.01 and 0.99 levels to reduce the influence of outliers. Table 2, Panel B provides the industry breakdown for fraud firms, IS and BS fraud firms, and the Compustat

[14] The results are robust to using an indicator variable for the firm's need for capital as computed in Dechow et al. (2011).

[15] Variable definitions and data sources are presented in Appendix 1.

population using the Fama and French 17 industry classification scheme. Fraud firms are distributed similarly to the Compustat population though relatively few firms in mining, oil, and banking commit fraud while more firms in the machinery and business equipment industry commit fraud. Considering fraud type, banks are more likely and firms in the machinery and business equipment industry are less likely to commit BS fraud[16].

4. EMPIRCAL ANALYSIS

4.1 Income Statement Fraud

I test Hypotheses 1A and 1B by estimating Cox proportional hazards models of the following form:

$$IS_{i,t} = \beta_1 PE\ MKT_t + \beta_2 DEFAULT\ RISK_t + \beta_3 GDP_t + \beta_4 SURPRISE_t + \beta_5 SEC_t + \beta_6 IS\ DETECT_t + \beta_7 IPOS_t + \beta_8 EARN\ SEN_{i,t-1} + \beta_9 KZ_{i,t-1} + \beta_{10} AB\ RET_{i,t-1} + \beta_{11} SIZE_{i,t-1} + \beta_{12} ROA_{i,t-1} + \beta_{13} IPO_{i,t} + \varepsilon_{i,t}. \quad (2)$$

The dependent variable, *IS*, takes a value of 1 the period income statement fraud begins and is 0 otherwise. *PE MKT*, *DEFAULT RISK*, *EARN SEN*, and *KZ* are as defined in Section 3. *GDP* is gross domestic product (inflation adjusted and expressed in 2005 $10s of billions) with the time trend removed using the Hodrick and Prescot (1997) filter. *SURPRISE*, computed as the difference between actual GDP and expected GDP as forecasted by the *Survey of Professional Forecasters* (Philadelphia FED), is included because the decision to commit fraud might be influenced by expected macroeconomic performance (Fernandes and Guedes 2010). *SEC* is the SEC's annual budget appropriation and controls for the SEC's ability to detect and litigate fraud. I also include *IS DETECT* which is the average time to detect IS frauds initiated in the current year. *IS DETECT* controls for changes in monitoring intensity.

[16] While banks face the same incentives as other firms to deliver strong earnings performance, the balance sheet of a bank is not comparable to that of firms in other industries. My results hold when excluding banks but this significantly reduces the BS fraud sample in particular. Since my hypotheses are the same for banks and non-banks and because I find no change in results between bank and non-bank frauds I include them to analyze as many frauds as possible.

IPOS is the number of initial public offerings in the current year. Macro variables are measured in year *t* to capture the environment in which the manager decides to commit fraud.

I include the following firm-level controls: *AB RET,* the firm's annual abnormal return; *SIZE,* the natural logarithm of market capitalization; *ROA,* operating income after depreciation scaled by average total assets; and *IPO,* an indicator variable equal to 1 if the firm had its initial public offering in the previous two years; zero otherwise. *IPO* is measured in the current year; lagging it would effectively change its definition to whether the firm made an initial public offering in the previous three years[17]. All other firm-level variables are measured as of the beginning of the year (lagged by one year) to capture the firm's circumstances at the beginning of the year the manager decides to commit fraud. A key reason for lagging firm-level variables is that restated data are not available for a large number of fraud firms and the fraudulently inflated numbers do not capture the underlying economics of the firm. Moreover, data of any sort are not available for a number of firms in the first year of fraud (particularly data required for *KZ* and *AB RET).*

A lack of restated financials presents a conceptual issue as it relates to *EARN SEN*. The relative sensitivity of a firm's price to earnings compared to the market can be calculated with non-restated data and it is preferable to capture this sensitivity in real time. That said, it is unlikely that a firm's price sensitivity to earnings is linear in earnings. Without knowing true earnings this calculation is noisy at best and biased at worst, therefore I choose to use the prior year's reported earnings in this calculation[18].

Table 3, Panel A presents estimates for three versions of equation (2): with macro variables only, firm-level variables only, and both macro and firm-level variables. As predicted, I find a positive and

[17] Results are not sensitive to measuring *IPO* in this way.

[18] Using restated data when it is available produces statistically and economically similar results but reduces the sample size. Another option is to use restated data when it is available and lagged data when it is not. While this also produces similar results, for consistency's sake I choose to measure *EARN SEN* in the same manner for all firms.

significant relation between *IS* and both *PE MKT* and *EARN SEN* (at the 0.01 level)[19]. The hazard ratios in the full model indicate that a one dollar increase in *PE MKT* is associated with a 5 percent increase in the probability of IS fraud; a 10 point increase in *EARN SEN* is associated with a 7 percent increase in the probability of IS fraud. Additionally, more managers commit IS fraud in periods with higher GDP, lower GDP surprise, and in years with more IPOs. Abnormal returns and firm size are both positively and significantly associated with IS fraud and there is weak evidence that managers at firms with recent IPOs are more likely to commit IS fraud (significant in one model and at the 0.10 level). When comparing coefficients across models a chi squared test indicates that the hazard rate for *PE MKT* is significantly smaller in the full model than it is in the macro model[20]. *EARN SEN* is not significantly different across models. The results provide support for Hypotheses 1A and 1B and suggest that both macro and firm-level incentives are important determinants of IS fraud. Additionally, the r-squared in the full model (31 percent) is notably larger than in the macro or firm-level model, further highlighting that both macro and firm-level conditions create incentives to commit IS fraud.

The survival models I estimate offer important advantages over probit/logit models in handling key features of the data, namely, right censoring, time at risk, and time-varying covariates. Right censoring occurs because not all ongoing frauds have been detected by the end of the sample period. Logit models treat these observations as if fraud will never occur while survival analysis is explicitly designed to take account of censoring. Time at risk is not accounted for with logit analysis. Logit analysis uses a dichotomous dependent variable for whether fraud occurs at any point in the study period. A fraud that begins after, say, ten years, could have begun during the first nine years; the fact that fraud did not occur in the first nine years is informative about fraud risk. Shumway (2001) shows that cross-sectional

[19] In the Cox model robust standard errors are equivalent to standard errors clustered by firm, so double clustering standard errors (by firm and year for example) is equivalent to clustering by year alone as the variance-covariance matrices of the specifications with robust and firm-clustered standard errors cancel each other out perfectly. Because of this, all Cox models present results clustered by firm. The z-statistics in models clustered by year are generally larger than those presented.

[20] This could be because fraud observations are lost when firm-level variables are added to the model. To consider this, I re-estimate models with macro variables alone including only firms for which firm-level data are available and find the results (presented in the Internet appendix) hold.

logit is an inconsistent estimator of the probability of failure because it does not account for time at risk. In contrast, time at risk (time to fraud) is the dependent variable in survival analysis.

4.2 Balance Sheet Fraud

I test Hypotheses 2A and 2B by estimating Cox proportional hazards models of the following form:

$$\begin{aligned} BS_{i,t} = {} & \beta_1 PE\ MKT_t + \beta_2 DEFAULT\ RISK_t + \beta_3 GDP_t + \beta_4 SURPRISE_t + \beta_5 SEC_t \\ & + \beta_6 BS\ DETECT_t + \beta_7 IPOS_t + \beta_8 EARN\ SEN_{i,t-1} + \beta_9 KZ_{i,t-1} \\ & + \beta_{10} AB\ RET_{i,t-1} + \beta_{11} SIZE_{i,t-1} + \beta_{12} ROA_{i,t-1} + \beta_{13} IPO_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

This model is similar to that which I use to test Hypotheses 1A and 1B except that the dependent variable is *BS*, which takes a value of 1 the period balance sheet fraud begins and is 0 otherwise, and *BS DETECT*, the average time to detect BS frauds initiated in the current year, replaces *IS DETECT*. Table 3, Panel B presents analogous results for estimations of equation (3).

As predicted, I find a positive and significant association between *BS* and both *DEFAULT RISK* and *KZ* (at the 0.01 level). In the full model, a one standard deviation increase in *DEFAULT RISK* is associated with at 42 percent increase in the probability of BS fraud; a one standard deviation increase in *KZ* is associated with a 45 percent increase in BS fraud. Firm size is positively associated with BS fraud; *ROA* is positively, but weakly, associated with BS fraud. The results suggest that both macro and firm-level variables explain significant variation in the incentives to commit BS fraud and provide strong evidence supporting Hypotheses 2A and 2B[21]. As with IS fraud, the r-squared in the full model of equation (3) is notably larger than that where either macro or firm-level variables are considered alone.

To further highlight the differences between IS and BS fraud I compare the parameter estimates from Table 3, Panels A and B, using a series of seemingly unrelated estimations. Table 3, Panel C

[21] I also estimate equations (2) and (3) including only firms where fraud ultimately took place. With this sample, hazard rates for IS and BS frauds are estimated using a sample of firms where fraud of any kind occurs. The results are provided in the Internet Appendix and are similar to those presented in Table 3, Panels A and B.

presents the results. The associations between IS fraud and both *PE MKT* and *EARN SEN* are significantly larger than they are for BS fraud (at the 0.05 level or better). Conversely, the associations between BS fraud and both *DEFAULT RISK* and *KZ* are significantly larger than they are for IS fraud (at the 0.01 level). The results indicate that IS and BS frauds are committed for different reasons and that incentives to commit IS fraud are not associated with BS fraud (and vice versa).

4.3 Alternative Samples

I re-estimate models with two additional samples to address concerns that results might be driven by changes in the detection and enforcement environments. The only changes are the dependent variable and whether the average time for detection of IS fraud or BS fraud is modeled; all other variables are as defined in Section 3[22].

Table 4 presents results using the DMZ sample; the first column models IS fraud and the second column models BS fraud. Consistent with Table 3, IS frauds in the DMZ sample are positively associated with *PE MKT* and *EARN SEN* (0.05 level or better). *DEFAULT RISK* and *KZ* are not significantly associated with IS fraud. BS frauds in the DMZ sample are positively associated with *DEFAULT RISK* and *KZ* (0.05 level or better) and are not significantly associated with *PE MKT* or *EARN SEN*. Both types of fraud in the DMZ sample are positively associated with firm size[23] but abnormal returns, which were strongly associated with IS fraud in the AAER sample, are not associated with IS fraud in the DMZ sample. The results provide more evidence in support of hypotheses 1 and 2 and more evidence that the documented associations are not related to omitted variables that can influence the AAER process.

[22] I also estimate equation (2) analyzing firms which received AAERs for violations other than fraud (insider trading, selling securities without a license) and find no association between the start period of the violation and my variables of interest. The results are provided in the Internet Appendix. This provides more evidence that different SEC violations occur during different macroeconomic periods and are associated with different firm-level characteristics.

[23] This is not surprising given that larger firms are more likely to face class action lawsuits.

Table 5 presents results using AAERs of frauds which were initially discovered by internal governance or by employee whistleblowers. The results are highly similar to those in Table 3. IS fraud is positively associated with *PE MKT, EARN SEN, GDP, IPOS, AB RET,* and *SIZE*, and negatively associated with *SURPRISE.* BS fraud is positively associated with *DEFAULT RISK, KZ,* and *SIZE,* and negatively associated with *IPOS.* That the results hold in the approximately 50 percent of frauds uncovered internally and through employee whistleblowers provides more support for hypotheses 1 and 2.

4.4 Robustness Analysis

King and Zeng (2001) note bias in binary analysis of rare events arises because: the statistical properties of binary regression models are not invariant to the (unconditional) mean of the dependent variable and because the method of computing probabilities of events in logistic analysis is suboptimal in finite samples of rare events. While I find significant results, the economic and statistical significance can be understated for variables for which I predict a weaker or insignificant association. King and Zeng develop a rare-events logit model which generates approximately unbiased and lower-variance estimates of logit coefficients and their variance-covariance matrix by correcting for small samples and rare events. While survival analysis is preferable to logit analysis for the reasons listed earlier, it is worth verifying the veracity of my results under an alternative specification specifically designed to deal with rare events. I estimate equations (2) and (3) using a rare events logit model and find the statistical significance of the results is unchanged[24].

Heinze and Schemper (2002) provide evidence that a method of penalized likelihood estimation develop by Firth (1993) that produces finite parameter estimates in cases where there are a small number of events can also be used to reduce the potential bias of maximum likelihood estimates. However this model assumes observations are independent; while this model is inappropriate for analysis with firm-level variables, it may be less concerning with regards to Hypotheses 1A and 2A, which deal with

[24] Results provided in the Internet Appendix.

macroeconomic incentives. I re-estimate equations (2) and (3) using penalized maximum likelihood including only macro variables and find the results are unchanged[25]

Table 3 provides evidence that the economic environment creates incentives for managers to commit fraud incremental to those at the firm-level. However, it is possible that these incentives might be better captured by measuring them at the industry level instead of the market level. While firms can be thought of as competing against all other firms in the market for shareholder interest, managers are often evaluated and compensated based on performance relative to industry peers (Antle and Smith 1986). Moreover, if the market is sensitive to earnings news in aggregate, it must also be sensitive to earnings news in most industries. There are not enough frauds to perform meaningful analyses within each industry,[26] and most industries are so highly correlated with the market that there is no meaningful time-series difference between market and industry level price sensitivity to earnings news. If countercyclical industries are looked at in aggregate, however, then there are enough cases of fraud to analyze and enough variation between market and industry level measures to investigate whether the incentives to commit fraud are better measured at the market or industry level.

To explore the possibility that industry measures are more relevant than market measures, I calculate *PE MKT* for the four industries[27] with earnings sensitivities negatively correlated with the market and re-estimate equations (2) and (3) for these industries. The results (not tabulated), from estimating equations (2) and (3) for countercyclical industries suggest that incentives to commit IS fraud are better measured using market level earnings sensitivity than using industry level earnings sensitivity[28].

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[25] Results provided in the Internet Appendix.

[26] Within the Fama-French 17 industry classification scheme there are fewer than 10 frauds in most industries and these frauds occur over a 25 year period

[27] The four industries are "Steel Works", "Fabricated Products", "Machinery and Business Equipment", and "Other". There is no clear industry level measure for *DEFAULT RISK* and *KZ* is not an industry dependent measure so these variables are unchanged.

[28] The association between IS fraud and earnings sensitivity is significantly larger when measured at the market level than at the industry level and when both market and industry measures are included in the same model market level earnings sensitivity remains positively and significantly associated with IS fraud while the association

While data limitations limit the scope of this analysis, results examining fraud in industries with countercyclical earnings sensitivity suggest that managers are responding to incentives at the market level and that these incentives are not simply proxies for industry level incentives.

4.5 Variation in Fraud Type Composition and Firm-level Associations through Time

The results in Tables 3 through 5 suggest that managers commit IS and BS frauds in different macroeconomic periods and in response to different incentives, and provide one possible explanation for inconsistencies found in prior research. To shed more light on this possibility I look at variation in fraud type over the sample period and perform further analyses over certain periods. Figure 3 shows the percentage of frauds per year that are defined as income statement or balance sheet. IS fraud is consistently higher than average in the mid to late 1990s and BS fraud is consistently lower than average during this period (though there are spikes and dips in individual years). Figure 3 indicates that a disproportionate percentage of frauds during the mid to late 1990s were income statement motivated. Figure 4 shows the percentage of aggregate IS and BS fraud that takes place each year. Approximately 51 percent of IS frauds occur in the 5 years from 1997-2001 while only 30 percent of BS frauds occur during this same period. BS fraud spikes relative to IS fraud in the late 1980s/early 1990s and in the late 2000s which are recessionary periods. The IS versus BS fraud profile changes over time. My results suggest this is an important consideration.

To investigate further, I estimate the following equation for all types of fraud over the following periods: 1986-1991, 1992-2000, and 2001-2010[29]:

$$FRAUD_{i,t} = \beta_1 EARN\ SEN_{i,t-1} + \beta_2 KZ_{i,t-1} + \beta_3 AB\ RET_{i,t-1} + \beta_4 SIZE_{i,t-1} + \beta_5 ROA_{i,t-1} + \beta_6 IPO_{i,t} + \varepsilon_{i,t}. \quad (4)$$

with industry level earnings sensitivity is not statistically significant. *PE MKT* is not significantly associated with BS fraud regardless of whether it is measured at the market or industry level.

[29] Results are not sensitive to varying the start and end periods one year in either direction.

Results are presented in Table 6[30]. The association between *FRAUD* and *EARN SEN* is positive and significant (at the 0.01 level) only in the 1992-2000 period. Further, it is actually negative and significant (though weakly) from 1986-1991. Conversely, *KZ* is positive and significantly associated with *FRAUD* from 1986-1991 and from 2001-2010 (at the 0.01 level). Additionally, the previously documented association between fraud and abnormal returns is confined to the period of 1992-2000. Most prior research analyzes samples where frauds occur between 1992 and 2000, but the incentives for fraud and the composition of fraud type during this period are significantly different than in periods before and after. Descriptive data and the results in Table 6 provide evidence regarding how associations between fraud and firm-level variables vary through time and signify the importance of considering the IS versus BS fraud composition of the sample.

To further illustrate the importance of sampling periods, I analyze the association between fraud and board of director independence in different time periods. Beasley (1996) and Dechow, Sloan, and Sweeney (1996) find a negative association between fraud and board independence while Agrawal and Chadha (2005) find no such association. These studies have several differences, including sampling methodology, and there are several possible explanations for the mixed results. However, one explanation is that the first two papers sample frauds from 1980-1992 while the third studies violations from 2000-2001. Given that director data from the earlier studies was hand collected and analyzed in matched samples I am not attempting a perfect replication, but instead am exploring whether this association varies over time using a sample of fraud firms collected using the same process in both time periods. I re-estimate equation (4) and add *IND*, the percentage of a firm's directors that are considered independent[31]. The results are presented in Table 7. In the full sample I find no association between fraud and director independence. However, for frauds initiated prior to 2000 I find a negative and significant (0.01 level) association between fraud and director independence, consistent with prior studies. Further, for frauds

[30] Results for models with firm-level variables alone are provided as the macro variables have little variation with so few years in the different samples.

[31] I exclude *IPO* from this estimation because only two fraud firms that have data on board independence in year t-1 had an IPO in the prior two years.

initiated after 1999 the association between fraud and board independence is actually positive, though not quite statistically significant. Again, while this is not meant to be a perfect replication of prior work, the results show that when sampling fraud under the same criterion the association between fraud and director independence varies drastically depending on which years the frauds are sampled from. This provides one explanation for the inconsistent results reported in prior studies.

5. SUMMARY AND CONCLUSIONS

I examine differences in both macro and firm-level incentives to commit income statement and balance sheet fraud. Income statement fraud tends to occur in periods of relatively high market price sensitivity to earnings news, and IS fraud firms are relatively more sensitive to idiosyncratic earnings performance. These associations are significantly larger than those for balance sheet fraud, which are not significantly greater than zero. In contrast, balance sheet fraud tends to occur during periods of relatively high default risk and BS fraud firms are more financially constrained. These associations are significantly larger than those for income statement fraud, which are not significantly greater zero. The results hold in samples of fraud derived from SEC AAERs, class action lawsuits, and a subsample of firms for which fraud was detected internally or by employee whistleblowers.

I document that associations between firm-level incentives and fraud vary through time. Frauds initiated between 1992 and 2000 are positively associated with firm-level earnings sensitivity; this period had a particularly large proportion of IS fraud. Frauds initiated between 1986 and 1991 are negatively associated with firm-level earnings sensitivity and frauds initiated between 2001 and 2010 are uncorrelated with firm-level earnings sensitivity. Conversely, frauds initiated between 1986 to 1991 or 2001 to 2010 are positively associated with firm financial constraints. These are periods with greater incidence of BS fraud. Frauds initiated between 1992 and 2000 are not associated with firm financial constraints. Further, the association between fraud and board independence is negative and significant for frauds initiated before 2000 but not significant (and actually positive) for frauds initiated after 1999.

These results indicate that managers commit different types of financial statement fraud in response to different incentives, which come from different (macro economy and firm-level) sources. Moreover, the strength of incentives to commit fraud varies over time.

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Appendix 1
Definition of Variables and Data Sources

Variable	Measurement	Source
Income Statement fraud *(IS)*	An indicator variable equal to 1 in the period the manager starts committing fraud in which all material manipulations are related to the Income Statement and 0 otherwise.	SEC AAERs
Balance Sheet fraud *(BS)*	An indicator variable equal to 1 in the period the manager starts committing fraud in which none of the material manipulations are related to the Income Statement and 0 otherwise.	SEC AAERs
Income Statement and Balance Sheet fraud *(ISBS)*	An indicator variable equal to 1 in the period the manager starts committing fraud with material manipulations both related and unrelated to the Income Statement and 0 otherwise.	SEC AAERs
Fraud *(FRAUD)*	An indicator variable equal to 1 in the period the manager starts committing fraud and 0 otherwise.	SEC AAERs
Non-fraud AAER Occurrence *(NFAAER)*	An indicator variable equal to 1 in the period the manager starts committing a non-fraud violation and 0 otherwise.	SEC AAERs
Market price sensitivity to earnings *(PE MKT)*	Value weighted price-earnings ratio for the market.	Compustat
Default risk premium *(DEFAULT*	Difference between the long term BAA corporate bond rate and the 10 year US Treasury rate.	St. Louis FED
Gross domestic product *(GDP)*	2005 GDP, inflation adjusted, expressed in $10s of billions and detrended using the Hodrick-Prescot filter.	Bureau of Economic Analysis
GDP Surprise *(SURPRISE)*	Difference between GDP and GDP forecast, as provided by the Philadelphia FED 'Survey of Professional Forecasters', expressed in $10s of billions.	Bureau of Economic Analysis and Philadelphia Fed
SEC budget *(SEC)*	The SEC's annual budget appropriation in $100s of millions.	SEC
Time to detect fraud *(DETECT)*	The average time in years to detect fraud initiated during the year.	SEC AAERs
Time to detect Income Statement fraud *(IS DETECT)*	The average time in years to detect Income Statement fraud initiated during the year.	SEC AAERs
Time to detect Balance Sheet fraud *(BS DETECT)*	The average time in years to detect Balance Sheet fraud initiated during the year.	SEC AAERs
Time to detect non-fraud violations *(NF DETECT)*	The average time in years to detect non-fraud violations initiated during the year.	SEC AAERs
Number of IPOs *(IPOS)*	The number of IPOs in the current year expressed in hundreds.	Jay Ritter's website http://bear.warrington.ufl.edu/ritter/

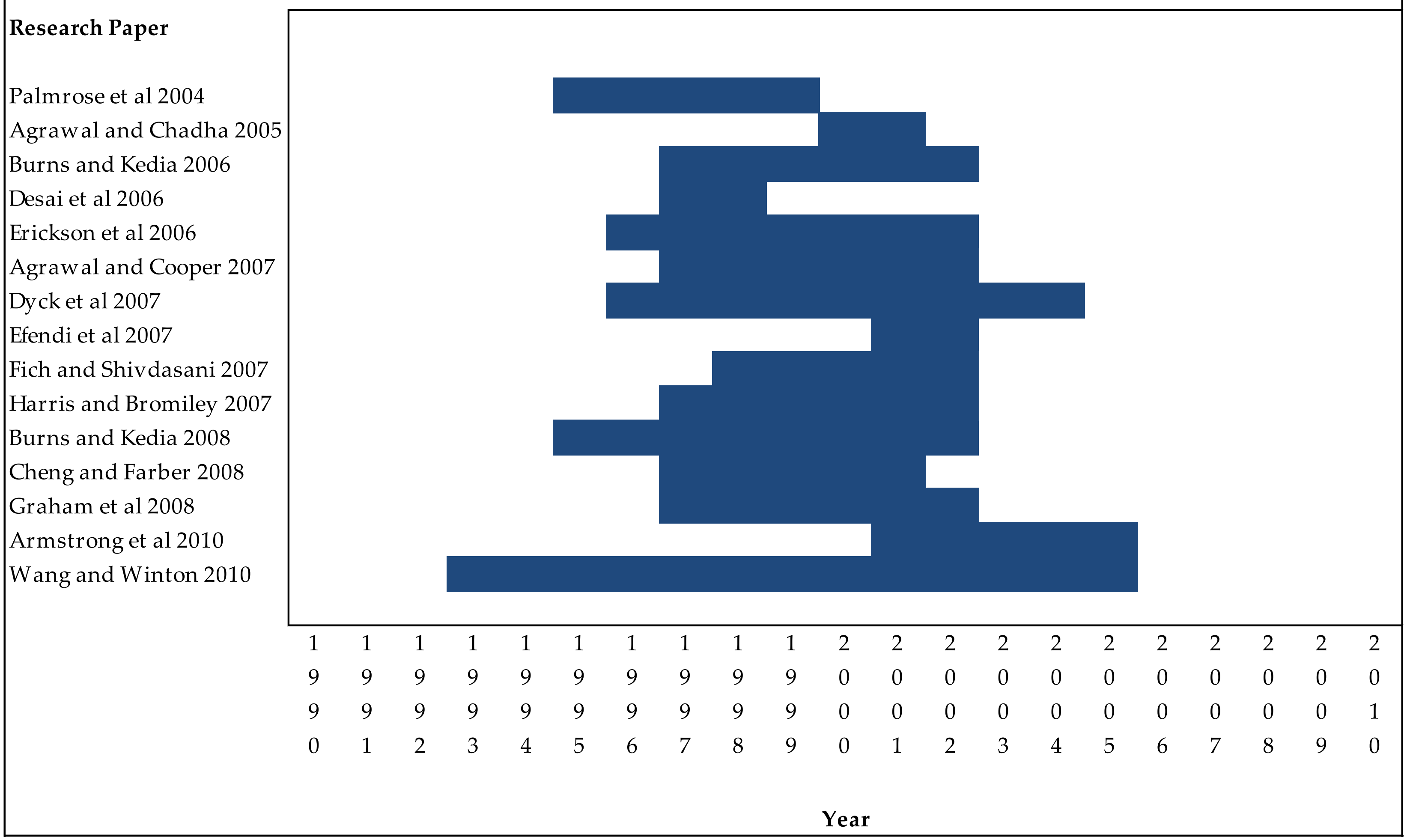
Appendix 1 - Continued

Variable	Measurement	Source
Relative earnings sensitivity *(EARN SEN)*	The annual percentile rank of the firm's price-earnings ratio.	Compustat
Financial constraint *(KZ)*	The financial constraint proxy developed by Kaplan and Zingales (1997). I construct the five variable KZ Score for each firm/year as the following linear combination: $KZ_{i,t} = -1.002\, CF_{i,t} / A_{i,t-1} - 39.368\, D_{i,t} / A_{i,t-1} - 1.315\, C_{i,t} / A_{i,t-1} + 3.139\, B_{i,t} + 0.283\, Q_{i,t}$ where $CF_{i,t} / A_{i,t-1}$ is cash flow over lagged assets; $D_{i,t} / A_{i,t-1}$ is cash dividends over lagged assets; $C_{i,t} / A_{i,t-1}$ is cash balances over lagged assets; $B_{i,t}$ is book leverage which is total debt divided by the sum of total debt and book equity measured at year-end, and $Q_{i,t}$ is Tobin's Q which is the market value of equity (price times shares outstanding) plus assets minus the book value of equity, divided by assets. All individual components of the above financial constraint variable are winsorized before constructing the variable.	Compustat
Abnormal returns *(AB RET)*	Annual firm return less the annual value weighted market return.	CRSP
Size *(SIZE)*	The natural logarithm of the firm's market capitalization.	Compustat
Performance *(ROA)*	Operating income before depreciation scaled by average total assets.	Compustat
Recent IPO *(IPO)*	An indicator variable equal to 1 if the firm has been listed on CRSP for less than 4 years and 0 otherwise.	CRSP
Board Independence *(IND)*	The percentage of independent directors on the firm's board of directors.	

Figure 1
Sample Sizes of Prior Research

Study	Fraud Firms used in Primary Analysis
Beasley 1996	75
Beatty, Liao, and Yu 1999	14
Beneish 1999	49
Beneish 1999	64
Brazel, Jones, and Zimbelman 2009	50
Cotter and Young 2007	56
Crutchley, Jensen, and Marshall 2007	97
Davidson, Dey, and Smith 2013	109
Dechow, Sloan, and Sweeney 1996	92
Dechow, Ge, Larson, and Sloan 2011	362
Erickson, Hanlon, and Maydew 2004	27
Erickson, Hanlon, and Maydew 2006	50
Feng, Ge, Luo, and Shevlin 2011	74
Fich and Shivdasani 2007	45
Gerety and Lehn 1997	62
Johnson,Ryan, and Tian 2009	87
Schrand and Zechman 2008	49

Figure 2: Timeline of Prior Research on Accounting Manipulations



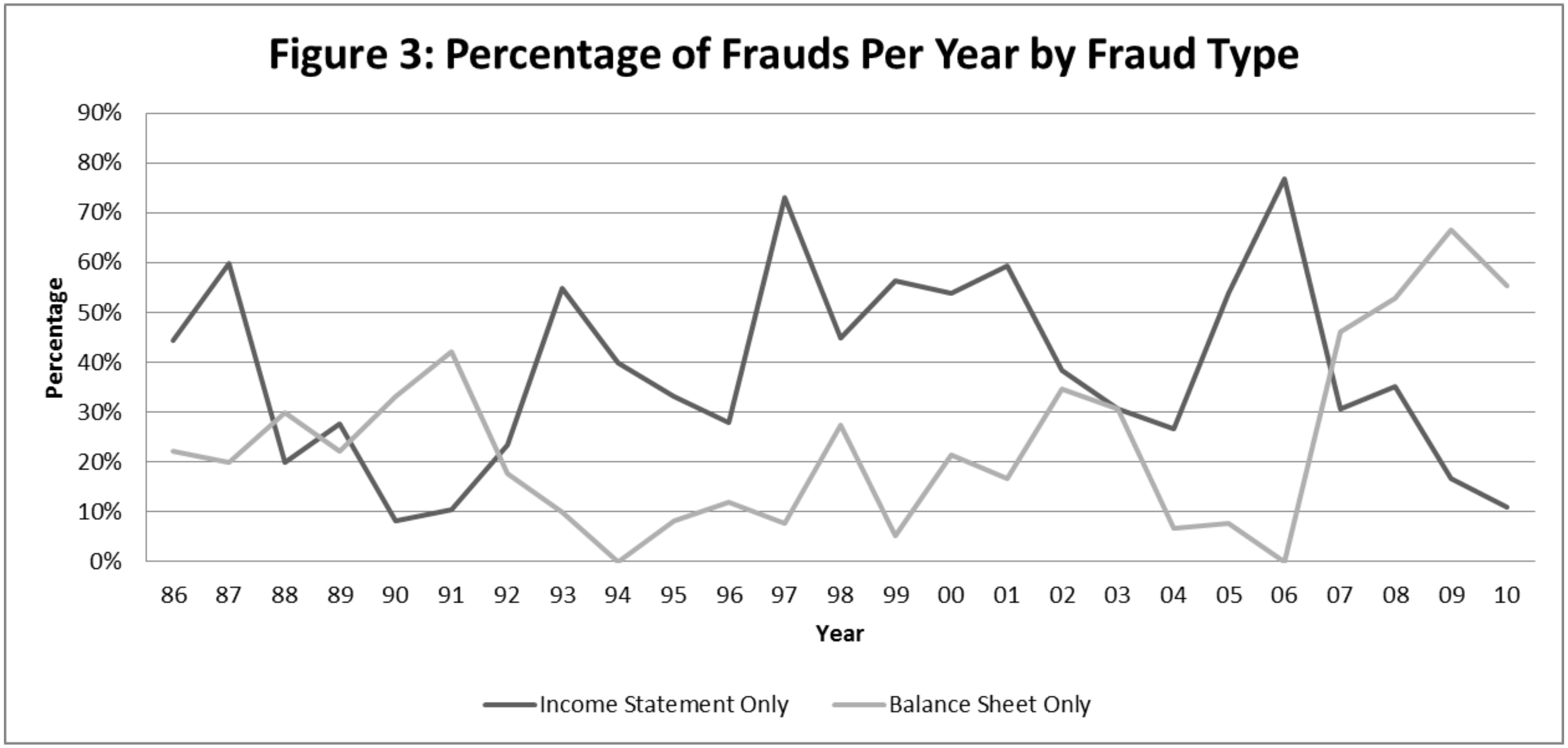


Figure 3: Percentage of Frauds Per Year by Fraud Type
Percentage
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
86 87 88 89 90 91 92 93 94 95 96 97 98 99 00 01 02 03 04 05 06 07 08 09 10
Year
Income Statement Only
Balance Sheet Only

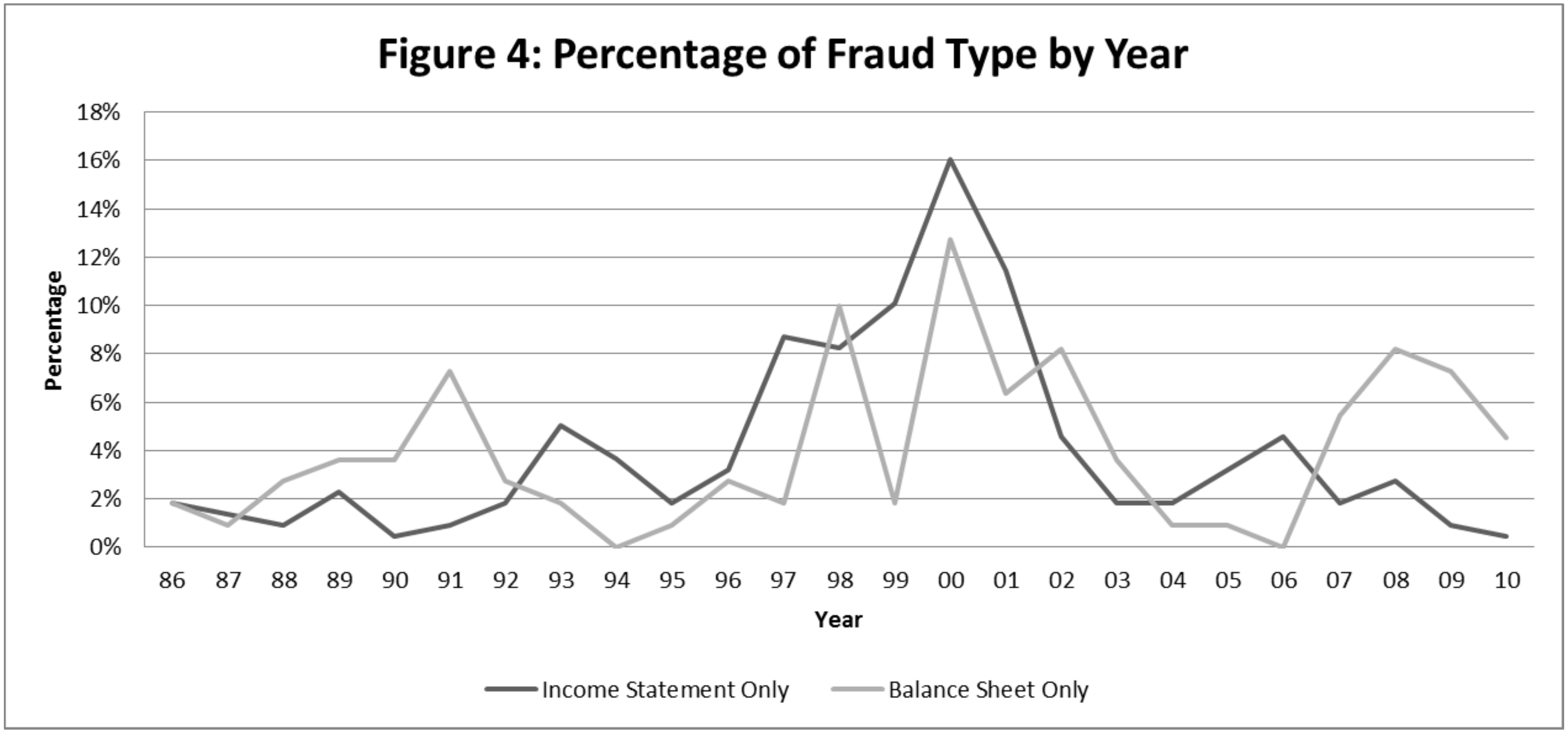


Figure 4: Percentage of Fraud Type by Year
18%
16%
14%
12%
10%
8%
6%
4%
2%
0%
Percentage
86 87 88 89 90 91 92 93 94 95 96 97 98 99 00 01 02 03 04 05 06 07 08 09 10
Year
Income Statement Only
Balance Sheet Only

Table 1
Sample Composition

Sample collection period	1986 - 2015
Sample period of violations	1986 - 2010
Total AAERs that involve specific firms	3,439
Less: AAERs unrelated to financial statament fraud	1,041
Less: redundant AAERs related to the same firm/incident	1,290
AAERs related to unique cases of financial statement fraud	1,108
Less: violations occurring after 2010 or before 1986	39
Less: firms without CRSP/Compustat identifiers	605
Less: earnings/net asset understatement	5
AAERs with unique CRSP/Compustat identifiers	459
Income statement only fraud firms	**189**
Income statement only fraud firms with CRSP/Compustat data in year prior to fraud	**161**
Balance sheet only fraud firms	**78**
Balance sheet only fraud firms with CRSP/Copmpustat data in year prior to fraud	**68**

Table 1 describes the AAER sample and collection process and notes how many firms are available for different analyses . The sample is reduced primarily because firms do not have CRSP/Compustat identifiers or because of missing data in the year before fraud began.

Table 2: Summary Statistics
Panel A: Descriptive Statistics

Macro Variables	Mean	Median		
PE MKT	23.30	20.06		
DEFAULT RISK	2.33	2.11		
GDP	1.27	1.73		
SURPRISE	-2.92	3.60		
SEC	4.80	3.28		
DETECT	2.73	2.68		
IS DETECT	2.60	2.52		
BS DETECT	2.71	2.57		
IPOS	2.61	1.73		
Firm Level Variables	Fraud Firms		Compustat	
	Mean	Median	Mean	Median
EARN SEN	55.8	58	49.21***	49***
KZ	0.83	0.77	0.57***	0.62***
AB RET	0.09	-0.01	0.01***	-0.07***
SIZE	5.92	5.94	5.01***	4.89***
ROA	0.10	0.11	0.06***	0.09**
IPO	0.11	0.00	0.07***	0.00
Firm Level Variables	Income Statement Fraud		Balance Sheet Fraud	
	Mean	Median	Mean	Median
EARN SEN	58.24	61.00	51.04***	53.00***
KZ	0.73	0.68	0.98***	0.91***
AB RET	0.12	0	0.05**	-0.03*
SIZE	5.89	5.86	5.99	6.13***
ROA	0.11	0.12	0.09***	0.08***
IPO	0.13	0.00	0.07***	0.00

Table 2, Panel A presents the mean and median of the macro variables and firm-level variables for the fraud firm samples and Compustat population. *PE MKT* is the value-weighted annual market price-earnings ratio; *DEFAULT RISK* is the difference between the long term BAA corporate bond rate and the 10 year treasury bill rate; *GDP* is gross domestic product (inflation adjusted and expressed in 2005 $10s of billions) detrended using the Hodrick and Prescot [1997] filter; *SURPRISE* is the difference between actual GDP and expected GDP; *SEC* is the SEC's annual budget appropriation; *DETECT* is the average time to detect frauds initiated in the current year; *IS DETECT* is the average time to detect IS frauds initiated in the current year; *BS DETECT* is the average time to detect BS frauds initiated in the current year; *IPOS* is the number of IPOs in the current year. *EARN SEN* is the percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997]; *AB RET* is the firm's annual abnormal return; *SIZE* is the natural logarithm of the firm's market capitalization; *ROA* is the firm's operating income after depreciation scaled by average total assets; *IPO* is an indicator that equals 1 if the firm made an initial public offering in the current or preceding two years and 0 otherwise. ***, **, and * denote significance at the .01, .05, and .10 levels respectively for t-tests (mean) and Wilcoxon/Chi-square (median) tests of differences.

Table 2: Summary Statistics
Panel B: Industry Composition of Fraud Firms and Compustat Population

Fama-French Industry	Fraud	Income Statement Fraud	Balance Sheet Fraud	Compustat
Food	4.79%	4.11%	2.83%	2.36%
Mining and Minerals	0.87%	0.00%	1.89%	5.07%
Oil and Petroleum Products	1.53%	0.91%	2.83%	6.18%
Textiles, Apparel and Footwear	3.70%	2.74%	5.66%	1.29%
Consumer Durables	2.18%	1.83%	3.77%	1.50%
Chemicals	0.87%	0.46%	1.89%	1.26%
Drugs, Soap, Perfum, Tobacco	4.58%	5.48%	2.83%	2.74%
Construction and Construction Materials	2.61%	1.37%	3.77%	2.63%
Steel Works	0.87%	0.00%	0.94%	0.93%
Fabricated Products	0.65%	0.00%	0.94%	0.60%
Machinery and Business Equipment	11.11%	18.72%	5.66%	6.88%
Automobiles	2.83%	1.83%	4.72%	1.02%
Transportation	5.66%	5.02%	4.72%	5.16%
Utilities	1.74%	0.46%	2.83%	1.95%
Retail Stores	6.54%	4.57%	5.66%	4.38%
Banks, Insurance Companies, and Other Financials	15.90%	7.31%	27.36%	26.63%
Other	33.55%	45.21%	21.70%	29.43%
	100.00%	100.00%	100.00%	100.00%

Table 2, Panel B presents the industry composition of the fraud firm samples and Compustat population using the Fama-French 17 industry classification scheme.

Table 3

Panel A: Survival Analysis - Income Statement Fraud

$$IS_{i,t} = \beta_1 PE\ MKT_t + \beta_2 DEFAULT\ RISK_t + \beta_3 GDP_t + \beta_4 SURPRISE_t + \beta_5 SEC_t + \beta_6 IS\ DETECT_t + \beta_7 IPOS_t + \beta_8 EARN\ SEN_{i,t-1} + \beta_9 KZ_{i,t-1} + \beta_{10} AB\ RET_{i,t-1} + \beta_{11} SIZE_{i,t-1} + \beta_{12} ROA_{i,t-1} + \beta_{13} IPO_{i,t} + \varepsilon_{i,t}$$

	MACRO	MICRO	FULL
PE MKT	1.078***		1.050***
	(4.72)		(4.14)
DEFAULT RISK	0.786		0.998
	(-0.88)		(-0.01)
GDP	1.021***		1.018***
	(2.92)		(2.85)
SURPRISE	0.979**		0.985**
	(-2.12)		(-2.15)
SEC	0.993		0.917
	(-0.11)		(-1.24)
IS DETECT	1.585		1.024
	(1.57)		(0.09)
IPOS	1.290***		1.208**
	(3.47)		(2.21)
EARN SEN		1.007***	1.007***
		(3.43)	(3.15)
KZ		1.061	1.084
		(0.72)	(0.80)
AB RET		1.334***	1.217***
		(3.60)	(2.62)
SIZE		1.247***	1.205***
		(5.11)	(4.20)
ROA		1.165	1.458
		(0.31)	(0.76)
IPO		1.884*	1.582
		(1.85)	(1.28)
OBSERVATIONS	155,753	109,113	109,113
FAILURES	189	161	161
R-SQUARED	0.26	0.20	0.31

CHI 2 - CROSS MODEL DIFFERENCE COMPARISONS	P VALUE
PE MKT Macro - *PE MKT* Full	0.074
DEFAULT RISK Macro - *DEFAULT RISK* Full	0.441
EARN SEN Micro - *EARN SEN* Full	0.636
KZ Micro - *KZ* Full	0.389

Table 3, Panel A - Continued

Table 3, Panel A presents the results of Cox proportional hazards models estimating variants of equation (2). Equation (2) estimates the relation between income statement fraud and macro and firm-level determinants. The first column models macroeconomic variables; the second column models firm-level variables; the third column models macroeconomic and firm-level variables. *PE MKT* is the value-weighted annual market price-earnings ratio; *DEFAULT RISK* is the difference between the long term BAA corporate bond rate and the 10 year treasury bill rate; *GDP* is gross domestic product (inflation adjusted and expressed in 2005 $10s of billions) detrended using the Hodrick and Prescot [1997] filter; *SURPRISE* is the difference between actual GDP and expected GDP; *SEC* is the SEC's annual budget appropriation; *IS DETECT* is the average time to detect IS frauds initiated in the current year; *IPOS* is the number of IPOs in the current year. *EARN SEN* is percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997]; *AB RET* is the firm's annual abnormal return; *SIZE* is the natural logarithm of the firm's market capitalization; *ROA* is the firm's operating income after depreciation scaled by average total assets; *IPO* is an indicator that equals 1 if the firm made an initial public offering in the current or preceding two years and 0 otherwise. Z-statistics appear in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels respectively.

Table 3

Panel B: Survival Analysis - Balance Sheet Fraud

$$BS_{i,t} = \beta_1 PE\ MKT_t + \beta_2 DEFAULT\ RISK_t + \beta_3 GDP_t + \beta_4 SURPRISE_t + \beta_5 SEC_t + \beta_6 BS\ DETECT_t + \beta_7 IPOS_t + \beta_8 EARN\ SEN_{i,t-1} + \beta_9 KZ_{i,t-1} + \beta_{10} AB\ RET_{i,t-1} + \beta_{11} SIZE_{i,t-1} + \beta_{12} ROA_{i,t-1} + \beta_{13} IPO_{i,t} + \varepsilon_{i,t}$$

	MACRO	MICRO	FULL
PE MKT	1.017		1.011
	(1.33)		(0.82)
DEFAULT RISK	1.528***		1.489***
	(2.86)		(3.06)
GDP	1.011		1.010
	(0.91)		(0.93)
SURPRISE	1.001		0.997
	(0.06)		(-0.22)
SEC	0.883		0.739***
	(-0.87)		(-2.82)
BS DETECT	0.827		0.882
	(-0.54)		(-0.58)
IPOS	0.820		0.716***
	(-1.58)		(-3.22)
EARN SEN		0.998	0.997
		(-0.39)	(-0.65)
KZ		1.291***	1.268***
		(3.27)	(3.40)
AB RET		0.681	0.694
		(-1.44)	(-1.40)
SIZE		1.197***	1.198***
		(2.70)	(2.62)
ROA		2.500*	2.806*
		(1.71)	(1.95)
IPO		0.270	0.305
		(-1.58)	(-1.44)
OBSERVATIONS	155,753	109,113	109,113
FAILURES	78	68	68
R-SQUARED	25	0.15	0.30

CHI 2 - CROSS MODEL DIFFERENCE COMPARISONS	P VALUE
PE MKT Macro - *PE MKT* Full	0.518
DEFAULT RISK Macro - *DEFAULT RISK* Full	0.464
EARN SEN Micro - *EARN SEN* Full	0.813
KZ Micro - *KZ* Full	0.317

Table 3, Panel B - Continued

Table 3, Panel B presents the results of Cox proportional hazards models estimating variants of equation (3). Equation (3) estimates the relation between balance sheet fraud and macro and firm-level determinants. The first column models macroeconomic variables; the second column models firm-level variables; the third column models macroeconomic and firm-level variables. *PE MKT* is the value-weighted annual market price-earnings ratio; *DEFAULT RISK* is the difference between the long term BAA corporate bond rate and the 10 year treasury bill rate; *GDP* is gross domestic product (inflation adjusted and expressed in 2005 $10s of billions) detrended using the Hodrick and Prescot [1997] filter; *SURPRISE* is the difference between actual GDP and expected GDP; *SEC* is the SEC's annual budget appropriation; *BS DETECT* is the average time to detect BS frauds initiated in the current year; *IPOS* is the number of IPOs in the current year. *EARN SEN* is percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997]; *AB RET* is the firm's annual abnormal return; *SIZE* is the natural logarithm of the firm's market capitalization; *ROA* is the firm's operating income after depreciation scaled by average total assets; *IPO* is an indicator that equals 1 if the firm made an initial public offering in the current or preceding two years and 0 otherwise. Z-statistics appear in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels respectively.

Table 3
Panel C: Coefficient Comparisons from Seemingly Unrelated Estimations

Income Statement Frauds Compared to Balance Sheet Frauds	
Variable	P Value
PE MKT	0.029
DEFAULT RISK	0.001
EARN SEN	0.001
KZ	0.002

Table 3, Panel C presents the P-values from Chi Squared tests comparing parameter estimates from a series of seemingly unrelated estimations. *PE MKT* is the value-weighted annual market price-earnings ratio; *DEFAULT RISK* is the difference between the long term BAA corporate bond rate and the 10 year treasury bill rate. *EARN SEN* is the percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997].

Table 4
Survival Analysis - Class Action Lawsuit Sample

$$IS|BS_{i,t} = \beta_1 PE\ MKT_t + \beta_2 DEFAULT\ RISK_t + \beta_3 GDP_t + \beta_4 SURPRISE_t + \beta_5 SEC_t + \beta_6 DETECT_t + \beta_7 IPOS_t + \beta_8 EARN\ SEN_{i,t-1} + \beta_9 KZ_{i,t-1} + \beta_{10} AB\ RET_{i,t-1} + \beta_{11} SIZE_{i,t-1} + \beta_{12} ROA_{i,t-1} + \beta_{13} IPO_{i,t} + \varepsilon_{i,t}$$

	IS FRAUD	BS FRAUD
PE MKT	1.143***	1.041
	(3.62)	(1.12)
DEFAULT RISK	0.595	1.247**
	(-0.54)	(2.05)
GDP	1.046**	0.994
	(2.23)	(-0.25)
SURPRISE	1.003	0.998
	(0.10)	(-0.05)
SEC	0.808	0.643**
	(-1.50)	(-2.11)
IS/BS DETECT	4.422***	0.534
	(3.19)	(-0.72)
IPOS	1.965***	1.087
	(3.44)	(0.43)
EARN SEN	1.006**	1.002
	(2.48)	(1.04)
KZ	1.106	1.424***
	(1.04)	(2.81)
AB RET	1.182	0.795
	(1.15)	(-1.54)
SIZE	2.061***	1.891***
	(11.17)	(5.60)
ROA	0.984	0.172**
	(-0.02)	(-2.06)
IPO	2.878	2.013
	(1.49)	(1.39)
OBSERVATIONS	109,113	109,113
FAILURES	62	28
R-SQUARED	0.61	0.21

CHI 2 - CROSS MODEL DIFFERENCE COMPARISONS	P VALUE
PE MKT IS - *PE MKT* BS	0.008
DEFAULT RISK IS - *DEFAULT RISK* BS	0.001
EARN SEN IS - *EARN SEN* BS	0.041
KZ IS - *KZ* BS	0.035

Table 4 - Continued

Table 4 presents the results of Cox proportional hazards models estimating variants of equations (2) and (3) using a sample of firms subject to class action lawsuits. Equation (2) estimates the relation between income statement fraud and macro and firm-level determinants. Equation (3) estimates the same relation but for balance sheet fraud. The first column models income statement fraud; the second column models balance sheet fraud. *PE MKT* is the value-weighted annual market price-earnings ratio; *DEFAULT RISK* is the difference between the long term BAA corporate bond rate and the 10 year treasury bill rate; *GDP* is gross domestic product (inflation adjusted and expressed in 2005 $10s of billions) detrended using the Hodrick and Prescot [1997] filter; *SURPRISE* is the difference between actual GDP and expected GDP; *SEC* is the SEC's annual budget appropriation; *IS DETECT* is the average time to detect IS frauds initiated in the current year; *IPOS* is the number of IPOs in the current year. *EARN SEN* is the percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997]; *AB RET* is the firm's annual abnormal return; *SIZE* is the natural logarithm of the firm's market capitalization; *ROA* is the firm's operating income after depreciation scaled by average total assets; *IPO* is an indicator that equals 1 if the firm made an initial public offering in the current or preceding two years and 0 otherwise. Z-statistics appear in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels respectively.

Table 5
Survival Analysis - Firm and Employee Detected Frauds

$$IS|BS_{i,t} = \beta_1 PE\ MKT_t + \beta_2 DEFAULT\ RISK_t + \beta_3 GDP_t + \beta_4 SURPRISE_t + \beta_5 SEC_t + \beta_6 DETECT_t + \beta_7 IPOS_t + \beta_8 EARN\ SEN_{i,t-1} + \beta_9 KZ_{i,t-1} + \beta_{10} AB\ RET_{i,t-1} + \beta_{11} SIZE_{i,t-1} + \beta_{12} ROA_{i,t-1} + \beta_{13} IPO_{i,t} + \varepsilon_{i,t}$$

	IS FRAUD	BS FRAUD
PE MKT	1.043***	1.017
	(3.85)	(1.06)
DEFAULT RISK	0.914	1.443***
	(-0.54)	(2.70)
GDP	1.024**	1.104
	(2.42)	(0.62)
SURPRISE	0.989**	0.999
	(-2.10)	(-0.18)
SEC	0.937	0.956
	(-1.19)	(-1.13)
IS/BS DETECT	1.034	0.974
	(0.60)	(-0.36)
IPOS	1.214**	0.842**
	(2.16)	(-2.16)
EARN SEN	1.008***	1.001
	(3.35)	(0.37)
KZ	1.064	1.349***
	(0.64)	(3.54)
AB RET	1.214**	0.748
	(2.49)	(-1.31)
SIZE	1.222***	1.208**
	(3.41)	(2.53)
ROA	1.351	2.218
	(0.64)	(1.57)
IPO	1.378	0.464
	(1.32)	(-1.18)
OBSERVATIONS	109,113	109,113
FAILURES	77	38
R-SQUARED	0.28	0.24

CHI 2 - CROSS MODEL DIFFERENCE COMPARISONS	P VALUE
PE MKT IS - *PE MKT* BS	0.037
DEFAULT RISK IS - *DEFAULT RISK* BS	0.001
EARN SEN IS - *EARN SEN* BS	0.001
KZ IS - *KZ* BS	0.001

Table 5 - Continued

Table 5 presents the results of Cox proportional hazards models estimating variants of equations (2) and (3) using a sample of firms for which managers or employees of the firm uncovered fraud. Equation (2) estimates the relation between income statement fraud and macro and firm-level determinants. Equation (3) estimates the same relation but for balance sheet fraud. The first column models income statement fraud; the second column models balance sheet fraud. *PE MKT* is the value-weighted annual market price-earnings ratio; *DEFAULT RISK* is the difference between the long term BAA corporate bond rate and the 10 year treasury bill rate; *GDP* is gross domestic product (inflation adjusted and expressed in 2005 $10s of billions) detrended using the Hodrick and Prescot [1997] filter; *SURPRISE* is the difference between actual GDP and expected GDP; *SEC* is the SEC's annual budget appropriation; *IS DETECT* is the average time to detect IS frauds initiated in the current year; *IPOS* is the number of IPOs in the current year. *EARN SEN* is the percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997]; *AB RET* is the firm's annual abnormal return; *SIZE* is the natural logarithm of the firm's market capitalization; *ROA* is the firm's operating income after depreciation scaled by average total assets; *IPO* is an indicator that equals 1 if the firm made an initial public offering in the current or preceding two years and 0 otherwise. Z-statistics appear in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels respectively.

Table 6
Survival Analysis By Time Period

$$FRAUD_{i,t} = \beta_1 EARN\ SEN_{i,t-1} + \beta_2 KZ_{i,t-1} + \beta_3 AB\ RET_{i,t-1} + \beta_4 SIZE_{i,t-1} + \beta_5 ROA_{i,t-1} + \beta_6 IPO_{i,t} + \varepsilon_{i,t}$$

	YEARS		
	1986-1991	1992-2000	2001-2010
EARN SEN	0.996*	1.007***	1.001
	(-1.86)	(3.14)	(0.36)
KZ	1.340***	1.081	1.228***
	(3.45)	(1.20)	(2.74)
AB RET	1.206	1.237***	0.992
	(0.43)	(2.90)	(-0.06)
SIZE	0.980	1.325***	1.077
	(-0.16)	(6.59)	(1.39)
ROA	9.260*	1.194	2.175
	(1.79)	(0.41)	(1.37)
IPO	0.691	0.942	1.999
	(-0.42)	(-0.20)	(1.39)
OBSERVATIONS	13,139	48,911	47,063
FAILURES	30	162	110
R-SQUARED	0.09	0.20	0.10

Table 6 presents the results of Cox proportional hazards models estimating equation (4). Equation (4) estimates the relation between fraud and firm-level determinants. The first column models 1986-1991; the second column models 1992-2000; the third column models 2001-2010. *EARN SEN* is the percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997]; *AB RET* is the firm's annual abnormal return; *SIZE* is the natural logarithm of the firm's market capitalization; *ROA* is the firm's operating income after depreciation scaled by average total assets; *IPO* is an indicator that equals 1 if the firm made an initial public offering in the current or preceding two years and 0 otherwise. Z-statistics appear in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels respectively.

Table 7
Survival Analysis By Time Period: Board Independence

$$FRAUD_{i,t} = \beta_1 IND_{i,t-1} + \beta_2 EARN\ SEN_{i,t-1} + \beta_3 KZ_{i,t-1} + \beta_4 AB\ RET_{i,t-1} + \beta_5 SIZE_{i,t-1} + \beta_6 ROA_{i,t} + \varepsilon_{i,t}$$

	YEARS		
	Full Sample	Pre 2000	Post 1999
IND	0.991	0.978***	1.013
	(-1.35)	(-3.13)	(1.59)
EARN SEN	1.003	1.005**	1.001
	(1.56)	(2.37)	(0.46)
KZ	1.203**	1.165*	1.250*
	(2.21)	(1.88)	(1.91)
AB RET	1.142	1.133	1.193
	(0.99)	(0.64)	(1.12)
SIZE	1.557***	1.709***	1.397***
	(5.58)	(5.32)	(2.58)
ROA	0.218*	0.523	0.105**
	(-1.90)	(-0.53)	(-2.18)
OBSERVATIONS	17,838	17,575	17,680
FAILURES	93	51	42
R-SQUARED	0.24	0.35	0.25

Table 7 presents the results of Cox proportional hazards models estimating equation (4). Equation (4) estimates the relation between fraud and firm-level determinants. The first column models the full sample; the second column models through 1999; the third column models after 1999. *IND* is the percentage of independent directors on the firm's board of directors. *EARN SEN* is the percentile rank of the firm's price-earnings ratio; *KZ* is the financial constraint proxy developed by Kaplan and Zingales [1997]; *AB RET* is the firm's annual abnormal return; *SIZE* is the natural logarithm of the firm's market capitalization; *ROA* is the firm's operating income after depreciation scaled by average total assets. Z-statistics appear in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels respectively.