BerkeleyHaas

Haas School of Business
University of California Berkeley

2016 CARE Conference
Perspectives on Fraud
August 5 -6, 2016
Panel 3:
Models for Predicting/Detecting Fraud

Patricia M. Dechow

Bernard Ebber and $11 billion Worldcom fraud

Kenneth Lay and Jeffrey Skilling 1B charge and Enron collapse

Financial Misstatement and Fraud

Martin Grass and Rite Aid and 2.3 billion fraud

Joseph Nacchio and 3B Revenue fraud at Qw

Ramalinga Raju Chairman 1.04B fraud at Satyam

Paul Allaire and Richard Thoman CEOs and 1.4B fraud at Xerox

Overview of academic perspective

Distinguishing between fraud and earnings management

FIGURE 1
The Distinction between Fraud and Earnings Management

	Accounting Choices	"Real" Cash Flow Choices
	Within GAAP	
"Conservative" Accounting	Overly aggressive recognition of provisions or reserves Overvaluation of acquired in-process R&D in purchase acquisitions Overstatement of restructuring charges and asset write-offs	Delaying sales Accelerating R&D or advertising expenditures
"Neutral" Earnings	Earnings that result from a neutral operation of the process	
"Aggressive" Accounting	Understatement of the provision for bad debts Drawing down provisions or reserves in an overly aggressive manner	Postponing R&D or advertising expenditures Accelerating sales
	Violates GAAP	
"Fraudulent" Accounting	Recording sales before they are "realizable" Recording fictitious sales Backdating sales invoices Overstating inventory by recording fictitious inventory	

Dechow and Skinner (2000)

Academics

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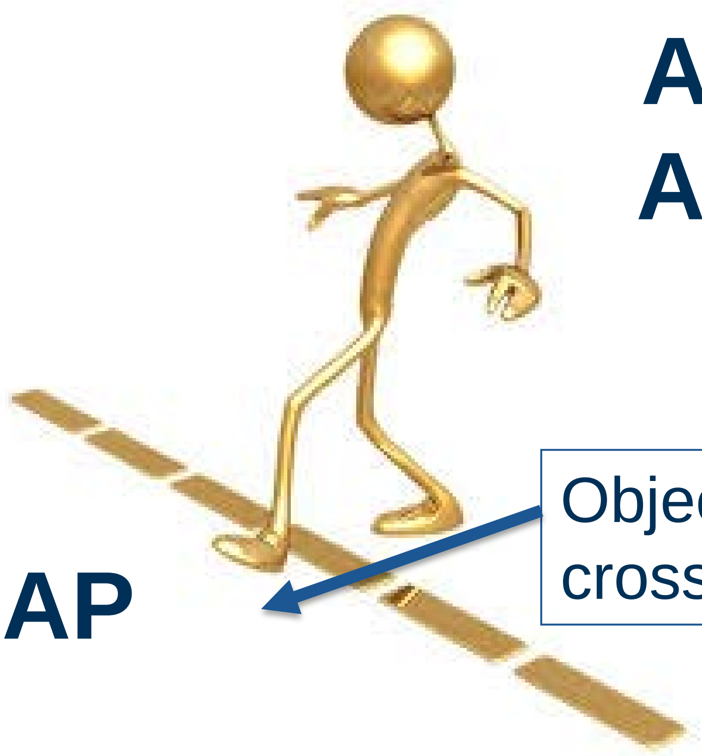
Academic research focuses on Motivations, causes and consequences

Dechow and Skinner (2000)

Regulator perspective

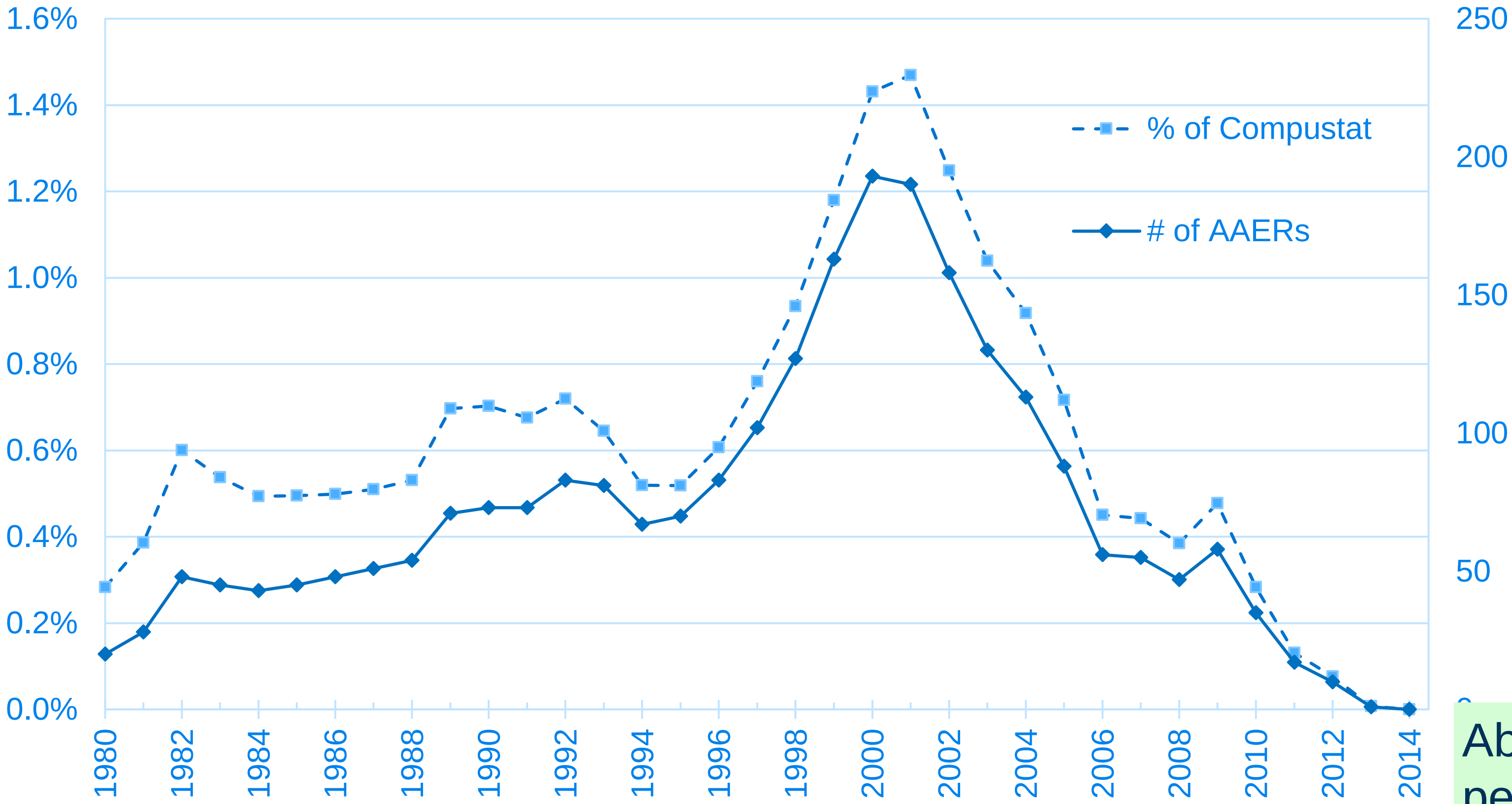
Aggressive Accounting



Objective: Who has crossed the line?

Violates GAAP

Manipulation years identified in AAERS

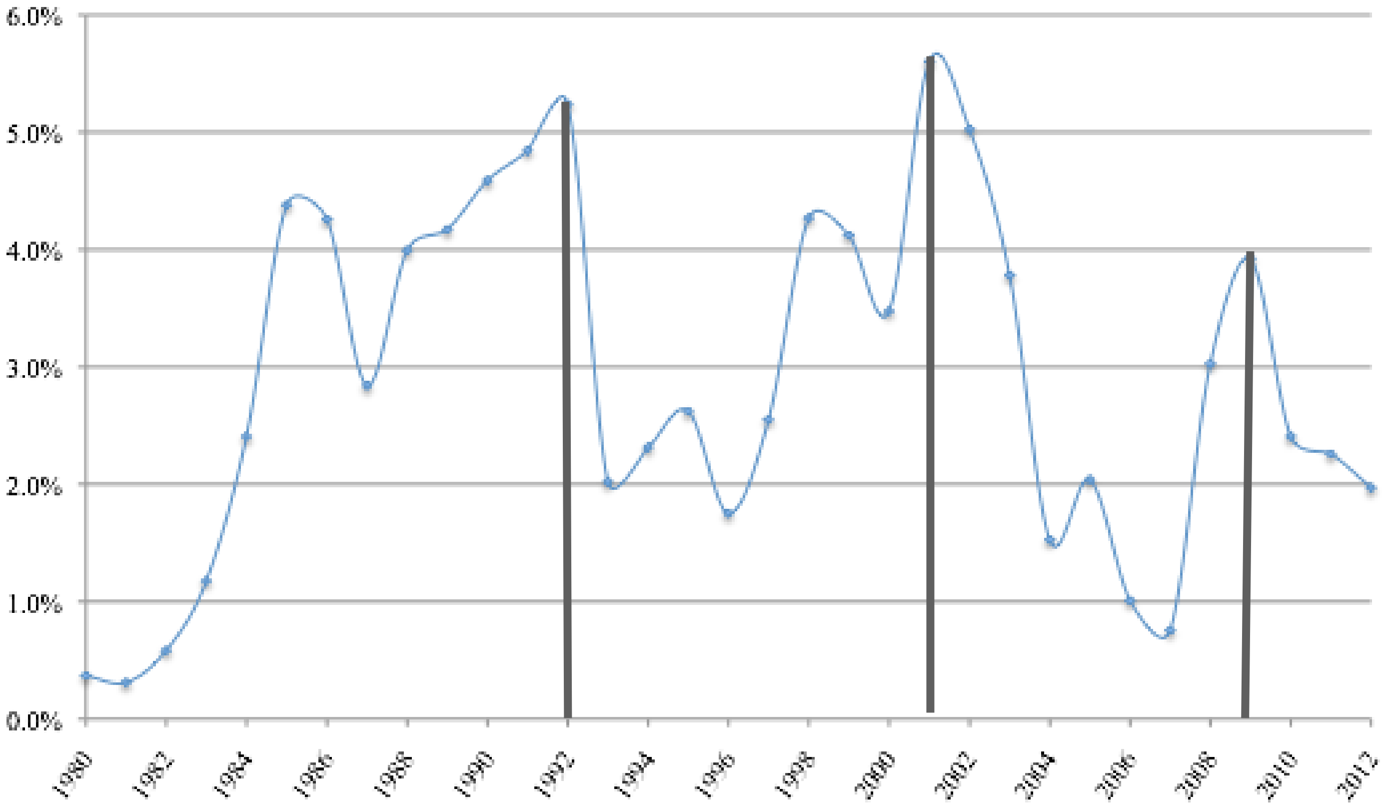


About half a percent of firm commit fraud each year

Note:
The percentage is calculated as follows: the number of firms that manipulated earnings in a particular year obtained from the AAER database (see CFRM: http://groups.haas.berkeley.edu/accounting/aaer_database/) divided by the number of firms in Compustat. The # of AAERs is the number of firms in the AAER database that manipulated earnings in a particular year.

Percentage of Firms going Bankrupt Performance- Related Delistings

About 3% of firms delist each year



Note:
The percentage is calculated as follows: the number of firms with performance related delistings divided by number of firms in CRSP. Sample universe is NYSE, AMEX, and NASDAQ firms. We define firms with performance related delistings if they have delisting code that is equal to 400 or between 550 and 585.

MODELS TO DETECT MANIPULATION

General overview

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Fraud Models: Financial and Governance Variables

Table 11. Predicting material earnings misstatements (samples based on SEC accounting and auditing enforcement releases (AAERs)).

Paper	Period	Treatment (*n*)	Non-treatment (*n*)	Accounting variables	Other variables[a]	Classification
Dechow et al. (1996)	1982–1992	92 firms	85 firms	**Accruals** **Accounting principles** **External financing**	**Board char.** **Director char.** **Covenant default**	Not reported
Beasley (1996)	1980–1991	75 firms	75 firms	Growth in assets (+) Indicator for persistent loss (+)	**Board char.** **Director char.**	15%
Beneish (1999)[b]	1982–1992	74 firms	2,332 firms	**RECT/SALE growth** (+) **Gross margin growth** (+) **NCA/AT** (+) **Sales growth** (–) Dep growth (+) SGA growth (–) Debt/AT growth (–) **Accruals/AT** (+)		Pseudo-R^2 = 37% 58% correctly classified[c]
Erickson et al. (2006)	1996–2003	50 firms	100 firms	Firms' desire for external financing (+) **Debt/AT** (+) BTM (–) P/E (+) ROA (–) **Sales growth (+)** Altman's Z (–)	CEO pay sensitivity (+) MV (+) Board char. Director char. Age of firm (–) M&A (+) **Stock volatility** (+)	Not reported
Dechow et al. (2011)	1982–2005	494 obs.	132,967 obs.	**RSST accruals** (+) **ΔRECT** (+) **ΔINVT** (+) **%Soft assets** (+) **ΔCash sales** (+) **ΔROA** (–)	**Issuance** (+) ΔEmp (–) **ΔOplease** (+) **Ret** (+) **Lag_Ret** (+)	69% correctly classified[d]
Feng et al. (2011)	1982–2005	116 obs.	219 obs.	F-score variables	**CEO pay sensitivity** (+) CFO pay sensitivity **CEO payslice** (+) **Director char.**	Not reported

M-score

CEO pay sensitivity not incrementally important

F-score

Chief Financial Officers are pressured by CEO

Source: Ak, Dechow, Sun and Wang (2013)

Fraud Models: Financial and Governance Variables

Table 11. (Continued)

Paper	Period	Treatment (*n*)	Non-treatment (*n*)	Accounting variables	Other variables[a]	Classification
Price et al. (2011)	1995–2008	444 obs.	48,376 obs.	WC accruals (+) M-score (+) **F-score** (+) Accruals quality (+) Disc. acc. (+) **Residual audit fees** (+)	**Audit integrity's accounting and governance risk score** (+)	Pseudo-R^2 = 12%
Hribar et al. (in press)	2000–2007	140 obs.	140 obs.	**Residual audit fees** (+) Accrual quality (–) **Abs_Disc. acc.** (–) Smooth (–) Std dev. of CFO (+) F-score variables	BTM (+)	Pseudo-R^2 = 11%

Compares commercial measures to Academic measures

Unexplained audit fees are incremental to F-Score

Significant variables are emboldened.

[a]Board char.: board of directors characteristics. Director char.: director characteristics.

[b]M-score = –4.840 + 0.920 × DSRI + 0.528 × GMI + 0.404 × AQ + 0.892 × SGI + 0.115 × DEPI – 0.172 × SGAI — 0.327 × LVGI + 4.697 × TATA

F-score = –7.893 +0.790 × rsst_acc + 2.518 × ch_rec + 1.191 × ch_inv + 1.979 × soft_assets + 0.171 × ch_cs –0.932 × ch_roa + 1.029 × issue

[c]Based on the M-score, the percentage of correctly classified manipulators ranges from 58–76%. The percentage of incorrectly classified nonmanipulators ranges from 7.6–17.5%.

[d]Based on the F-score, the percentage of correctly classified manipulators is 69%. The percentage of incorrectly classified nonmanipulators is 36%.

Classification Accuracy of Models

TABLE 7 (Continued)

Panel C: *F*-score cutoff set at 1.00

	Model 1 predicted		
Observed	Misstate	No-misstate	
Misstate	**339**	155	494
No-misstate	48,282	**84,685**	132,967
	48,621	84,840	**133,461**
Misstate	**68.6%**	31.4%	0.4%
No-Misstate	36.3%	**63.7%**	99.6%
Correct classification		63.71% (1)	
Sensitivity		68.62% (2)	
Type I errors		36.31% (3)	
Type II errors		31.38% (4)	

Notes:

(1) Correct classification is calculated as [(339 + 84,685)/133,4

(2) Sensitivity is calculated as (339/494).

(3) Type I errors are calculated as (48,282/132,967).

(4) Type II errors are calculated as (155/494).

Models detect fraud firms, but a lot of firms classified as fraud firms do not end up in the SEC sample

Source: Dechow, Ge, Larson, and Sloan (2011)

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Correct classification; fraud and non-fraud firms correctly classified out of the total firms.

Perfect model: 100% accuracy

Source: Dechow, Ge, Larson, and Sloan (2011)

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Sensitivity: % of fraud firms correctly identified

Sensitivity tells us how good the model is given the cut-off
Higher is better.

Source: Dechow, Ge, Larson, and Sloan (2011)

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Type I errors:
% of non-fraud that are classified as fraud firms

"innocent man goes to jail"

A lot of firms classified as fraud firms do not end up in the SEC sample.

- **Costs**
- SEC investigation with no outcome
- Audit firm does not accept a client

Source: Dechow, Ge, Larson, and Sloan (2011)

Classification Accuracy of Models

TABLE 7 (Continued)

Panel C: *F*-score cutoff set at 1.00

Observed	Model 1 predicted: Misstate	Model 1 predicted: No-misstate	
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Type II errors:
% of fraud firms that are classified as non-fraud firms

"*Thief that got away*"

Cost of Type II errors
- When fraud is revealed…
- Audit firm get sued
- Regulator is criticized
- Investors lose money

- Lowering the cutoff will reduce Type II errors but increase Type I errors

Source: Dechow, Ge, Larson, and Sloan (2011)

Fraud Models Continued: Computer intensive approaches.

Amiram, Bozanic and Rouen (2015)

Benfords Law: First digit of numbers in Financial Statements

More 1's than 9's

1	2	3	4	5	6	7	8	9
0.301	0.1761	0.1249	0.0969	0.0792	0.0669	0.058	0.0512	0.0458

Distribution of monthly returns from investing in Bernie Madoff's fund

1	2	3	4	5	6	7	8	9
0.396	0.142	0.104	0.071	0.075	0.066	0.061	0.066	0.019

Much higher than expected

Fraud Models: Benford's Law..

Amiram, Bozanic and Rouen (2015)

Table 10 FSD_Score and material misstatements

$$\begin{aligned}\text{AAER}_{i,t} = \alpha &+ \beta_1\text{FSD\_Score} + \beta_2\text{ABS\_JONES\_RESID}_{i,t} + \beta_3\text{STD\_DD\_RESID}_{i,t}\\ &+ \beta_4\text{MANIPULATOR}_{i,t} + \beta_5\text{F\_SCORE}_{i,t} + \beta_6\text{ABS\_WCACC}_{i,t} + \beta_7\text{ABS\_RSST}_{i,t}\\ &+ \beta_8\text{CH\_CS}_{i,t} + \beta_9\text{CH\_ROA}_{i,t} + \beta_{10}\text{SOFT\_ASSETS}_{i,t} + \beta_{11}ISSUE_{i,t} + \beta_{12}MTB_{i,t}\\ &+ \beta_{13}AT_{i,t} + \varepsilon_{i,t}\end{aligned}$$

Variable	AAER		
	(1)	(2)	(3)
FSD_Score	−40.691***		
	(−3.87)		
FSD_Score_{t-1}		21.963*	
		(1.80)	
FSD_Score_{t-2}			39.222***
ABS_JONES_RESID	−1.078	−1.074	−1.059
	(−1.38)	(−1.33)	(−1.32)
STD_DD_RESID	0.011	−0.171	−0.191
	(0.02)	(−0.27)	(−0.32)
MANIPULATOR	0.122	0.116	0.109
	(0.48)	(0.45)	(0.44)
F_SCORE	1.980***	1.978***	1.994***
	(5.88)	(5.80)	(5.58)
ABS_WCACC	−1.233	−1.613	−1.702
	(−0.78)	(−1.02)	(−1.09)
ABS_RSST	0.401	0.356	0.274
	(0.83)	(0.75)	(0.57)

Fraud Models: Machine Learning

Cecchini, Aytug, Koehler, Pathak (2010)

- Identify 23 financial statement variables used in prior research
- Have the computer learn on early data

the results of other studies on these data is shown in the next section). The novelty of our research is the nonlinear mapping of the attributes by the financial kernel into relevant features combined with the structural risk minimization offered by the SVM. In the following section we compare our results to other leading fraud detection research.

Fraud Models: Machine Learning

Cecchini, Aytug, Koehler, Pathak (2010)

Cecchini et al.: *Detecting Management Fraud in Public Companies*
Management Science 56(7), pp. 1146–1160, © 2010 INFORMS

Table 6 Comparison of Results with Previous Fraud Detection Methods

Author(s)	Method	Recall: Percentage correct—(sample size)	Results on training or test set	Type of data
Loebbecke et al. (1989)	Assessment model	86—Fraud (77)	Training	Nonpublic data
Hansen et al. (1996)	Qualitative response model	56—Fraud (77) 90—Nonfraud (305)	Test	Nonpublic data
Bell and Carcello (2000)	Logistic regression	81—Fraud (77) 86—Nonfraud (305)	Test	Nonpublic data
Beneish (1999)	Probit	56—Fraud (74) 90.2—Nonfraud (2,332)	Test	Publicly available data
Summers and Sweeney (1998)	Logistic regression	67—Fraud (51) ?— Nonfraud (51)	Training	Publicly available data
Green and Choi (1997)	Neural network	74—Fraud (46) 68.4—Nonfraud (49)	Test	Publicly available data
Dechow et al. (2009)	Logistic regression	64.5—Fraud (293) 66.35—Nonfraud (79,358)	Test	Publicly available data
Cecchini et al 2010	SVM-FK	80.0—Fraud (132) 90.6—Nonfraud (3,187)	Test	Publicly available data

Fraud Models: Machine Learning

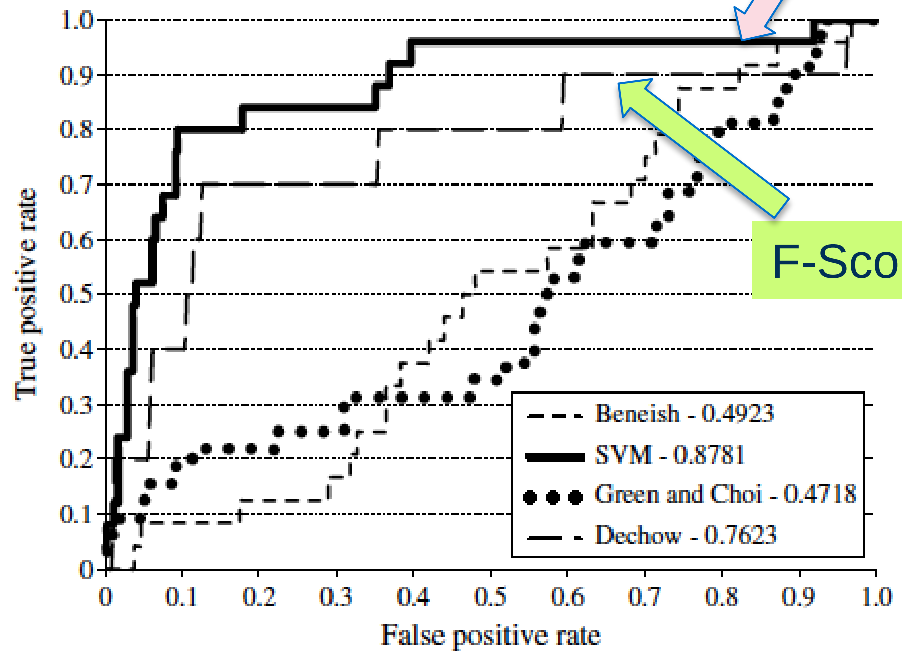
Table 7 Comparative Results Using the Same Data Set

Author(s)	Method	Final sample size (after excluding firms with missing values)	Percentage correct	AUC
Beneish (1999)	Probit	149 Fraud 3,389 Nonfraud	54.2 Fraud 45.5 Nonfraud	0.492
Green and Choi (1997)	Neural network	192 Fraud 3,173 Nonfraud	100.0 Fraud 7.1 Nonfraud	0.472
Dechow et al. (2009)	Logistic regression	57 Fraud 1,244 Nonfraud	70.0 Fraud 84.9 Nonfraud	0.762
This paper	SVM-FK	132 Fraud 3,187 Nonfraud	80.0 Fraud 90.6 Nonfraud	0.878

Replicating models using same dataset

Machine-Learning

Figure 1 ROC Curve Comparing Research Methodologies



F-Score

Fraud Models: Nonfinancial Measures

Brazel, Jones, and Zimmerman (2009)

$$CAPACITY\ DIFF_t = REVENUE\ GROWTH_t - NFM\ GROWTH_t$$

where,

$$\begin{aligned}
REVENUE\ GROWTH &= (\text{Revenue}_t - \text{Revenue}_{t-1})/\text{Revenue}_{t-1} \\
NFM\ GROWTH &= (NFM_t - NFM_{t-1})/NFM_{t-1} \\
REVENUE &= \text{total revenue} \\
NFM &= \text{nonfinancial measure} \\
t &= \text{initial year of the fraud}
\end{aligned}$$

NFM – students collected up to four measures for fraud firm and a matched firm. Examples, number of stores, square feet of floor space, energy producing capacity

Fraud Models: Nonfinancial Measures

Brazel, Jones, and Zimmerman (2009)

TABLE 5

Logistic Regression Comparing 50 Fraud Firms with 50 Matched Competitors (H2 Testing for CAPACITY DIFF)

Variables	Predicted Sign	Parameter Estimate	*p-value*
INTERCEPT		−0.96	0.63
CAPACITY DIFF	+	1.43	0.04
FINANCING	+	0.09	0.96
LEVERAGE	+	1.58	0.18
ALTMAN'S Z SCORE	+	0.01	0.89
MARKET VALUE OF EQUITY	?	0.00	0.82
BOOK TO MARKET	?	0.01	0.99
EARNINGS TO PRICE	?	1.40	0.44
RETURN ON ASSETS	?	−5.58	0.08
AGE OF FIRM	−	−0.04	0.06
M&A IN YEAR OF FRAUD	+	0.76	0.35
BIG FOUR	−	1.37	0.16
INSIDERS ON BOARD	+	−1.10	0.64
CEO = COB	+	0.57	0.47
TOTAL ACCRUALS	+	6.00	0.07
SPECIAL ITEMS	+	0.19	0.75
REVENUE GROWTH	+	−0.36	0.60
TOTAL ASSETS	?	0.00	0.73
NEGATIVE CHANGE IN NFM	+	−0.86	0.18
Sample Size			100

NFM – students collected up to four measures for fraud firm and a matched firm. Examples, number of stores, square feet of floor space, energy producing capacity

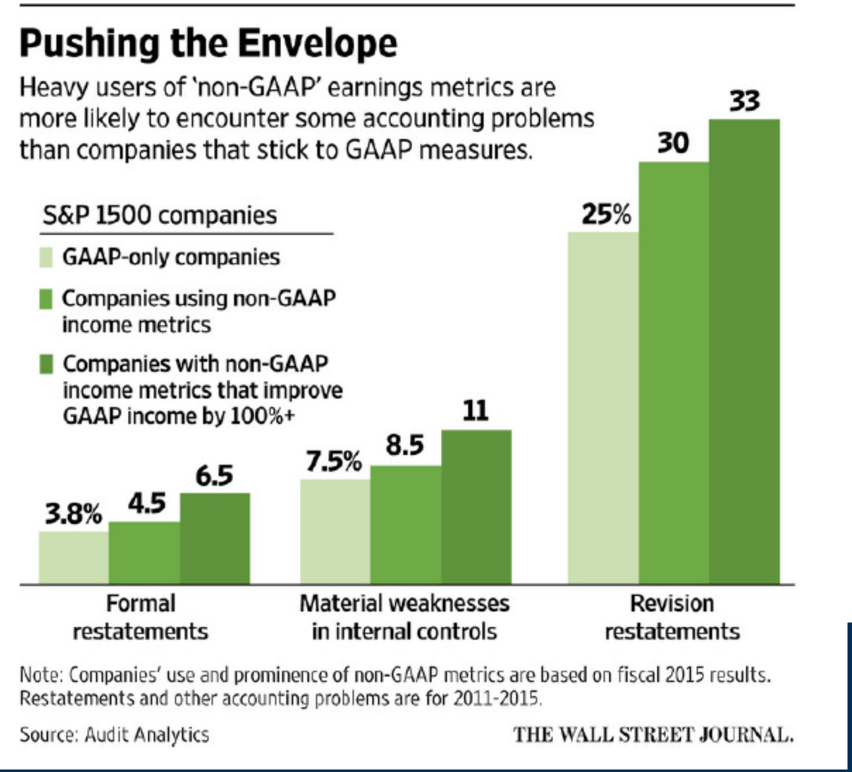
Fraud Models:
Other sources of Information

- “Deceptive words in conference calls” (Larcker and Zakolyukina 2012)
- Fraud Detection Using Vocal, Linguistic, and Financial Cues” (Throckmorton, Mayew, Collins and Venkatachalam 2015)
- Executive off the job behavior - Luxury goods and prior legal infractions (Davidson, Dey, Smith 2012)

Fraud Models: Managing Market Expectations..

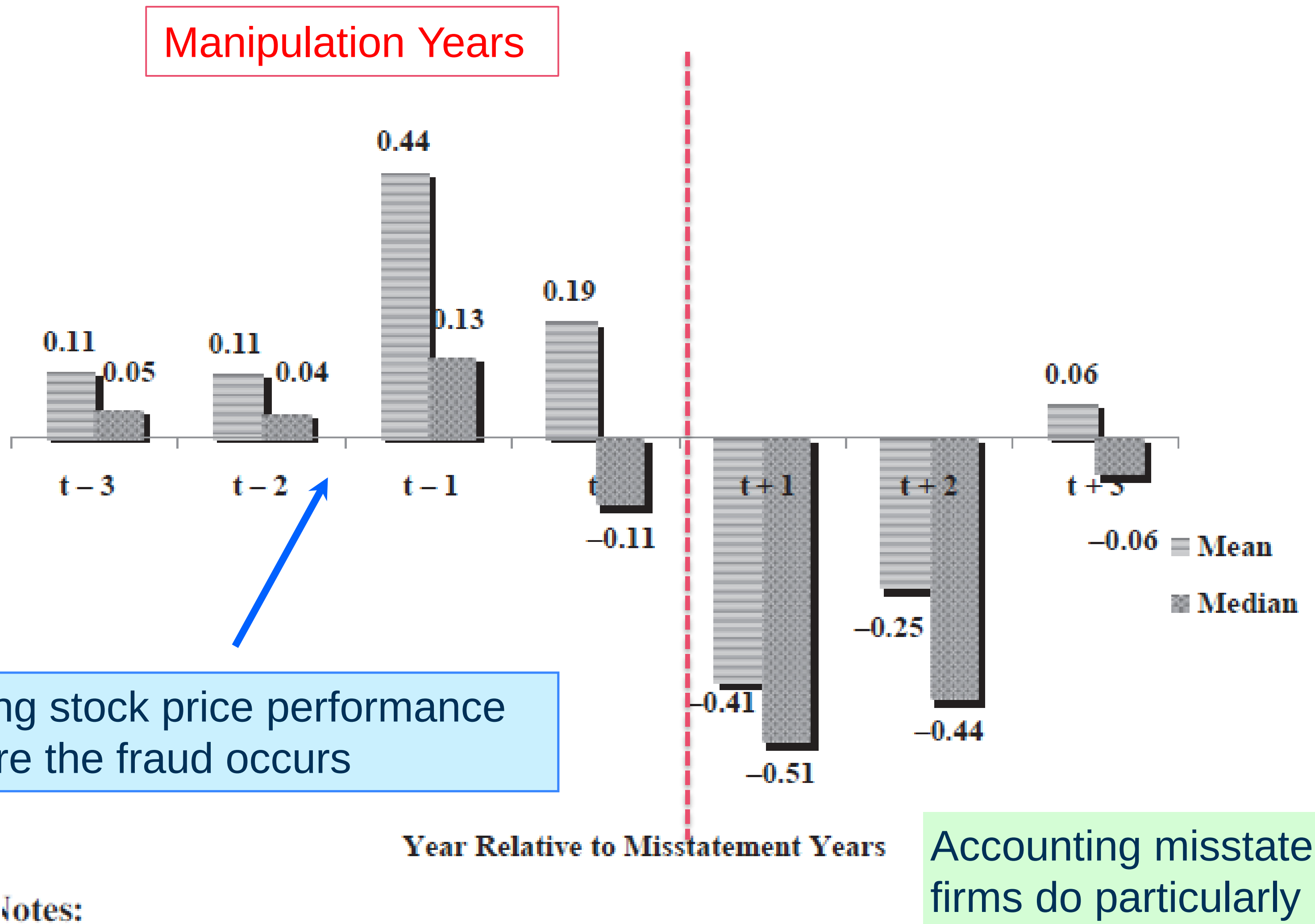
- Manipulating firms (AAER firms) are more likely to consistently beat analyst expectations for up to 8 quarters than propensity matched firms (Chu, Dechow, Hui, Wang 2016)
- Firms that use non-GAAP earnings are more likely to restate.

Audit Analytics – WSJ August 4,



Does stock market anticipate manipulation?

Stock returns and Misstatements



Strong stock price performance before the fraud occurs

Accounting misstatements firms do particularly poorly after manipulation stops

Source: Dechow, Ge, Larson, Sloan (2011), Figure 1.

Table 1. Investor response to corporate events.

Event	Corporate event short-window announcement returns	Future long-run returns after corporate event announcements
Default[a]	–3.5%	N/A
Bankruptcy[b]	–21.7%	N/A
Predicted distress[c]	N/A	–17.9%
Goodwill impairment[d]	–1.8%	N/A
Predicted goodwill impairment[e]	N/A	–21.7%
Restructuring charges[f]	0.6%	–7.6%
Special items[g]	–0.3%	17.0%
SEOs[h]	–2.0%	–7.4%
IPOs[i]	14.0%	–7.0%
Misstatement[j]	–9.0%	N/A
Predicted material misstatement[k]	N/A	–7.5%

Future long-run returns are measured over the annual interval. N/A: not applicable or not examined in this review.
The sources of each corporate event:
[a]Beneish and Press (1995).
[b]Lang and Stulz (1992).
[c]Campbell et al. (2008).
[d]Li and Sloan (2012: table 5).
[e]Li and Sloan (2012: table 8, panel B).
[f]Restructuring charges announcement return: Lee (2013: table 4, panel B). The 0.6% is conditioned on observations in the post-SFAS 146 period. Restructuring charges long-run return: Bhojraj et al. (2009: table 3, panel B). The –7.6% is conditioned on firms with large restructuring charges in the post-SFAS 146 period.
[g]Special items announcement return: Francis et al. (1996: table 3). Special items (write-offs) are generally revealed at the time of earnings announcements and so the individual impact is difficult to isolate. Our own estimate is –0.3%. Special items long-run return: Dechow and Ge (2006: table 3, panel B). The 17.0% is conditioned on firms with low accruals and large negative special items.
[h]SEOs: Ritter (2003), and Rangan (1998).
[i]IPOs: Loughran and Ritter (2002), and Ritter (2013). The –7.0% is based on the finding of a –20.0% cumulative three-year market-adjusted buy-and-hold return.
[j]Misstatement announcement: Dechow et al. (1996).
[k]Predicted material misstatement: Beneish et al. (2012: table 2).

Accounting misstatements are a very negative signal to market

Summary: Fraud Models

- Detection: Financial ratios help – Accruals, receivables, inventory, ROA,
- Computer intensive functions also appear to help – Benfords law, machine learning, text analysis, etc.,
- Non-financial measures help – but not comprehensively studied due to data collection issues.
- Firms relation with stock market – prior returns, conference calls, non-GAAP earnings, consistent beating of earnings expectations, raising financing
- Management characteristics – risk takers, ego, crime, founder, power
- Governance – board characteristics
- Management Incentives

Summary of Academic Models

- Academics focus on understanding incentives of managers, causes, and consequences.
- Many papers do not directly address whether the model improves fraud detection (correct classification, sensitivity, type I, type II errors)
- From a practical perspective (Regulators, Auditors, director insurance, etc.,) such tests would be helpful.

THANK YOU!