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Risk Assessment Perspectives for Forensic Accountants and Auditors Based on Some International Evidence

Hugh Grove
Mac Clouse
*Adam Greiner**

Introduction

Managing and assessing risk should be a core strategic competency for any international company (Coleman, 2011). Fraudulent financial reporting has been an issue since the advent of financial statements. This type of fraud costs approximately one trillion dollars per year in the United States (ACFE, 2014). The purpose of this paper is to develop and apply risk assessment screening guidelines using common statistical analyses and follow-up procedures. These guidelines are based primarily on the work of financial analysts, forensic accountants, and short sellers, involving major financial reporting frauds of the 21st Century (Grove and Basilico, 2011) and major Chinese reporting frauds (Grove and Clouse, 2014). We demonstrate that fraud is an international concern.

Despite heightened concern after the financial scandals and economic crisis, Howard Schilit, a forensic accountant and financial analyst, has observed: "I read recently that the one lesson we have learned from history is that we have learned nothing from history. Yet my mantra remains that in order to find fraud, we must study the history of fraud. A common element in major frauds is that their warning signs were not hard to find; in fact, they were hard to miss" (Schilit, 2010). Hence, risk analysis is a key concern of forensic accountants, auditors, and board members in order to assess the possibility of fraud in any organization. Fraud risk management helps management and Boards of Directors identify misconduct, gain insight into enhanced internal fraud assessments, improve business operations, and achieve quality reporting.

Dangers of inadequate risk assessment for investors reflect disparity between market cap destructions and very small cash settlements paid by management, underwriters, and auditors in shareholder class action lawsuits involving the Chinese initial public offering (IPO) and reverse merger companies. For example, two international billionaire investors lost more than one billion dollars in Sino-Forest investments: $750 million by John Paulson (Struck, 2011), and $300 million by Richard Chandler (Koven, 2011). Sino-Forest's underwriters, who helped the company raise three billion dollars over the years, paid $32.5 million and Sino-Forest's auditors paid $117 million to settle an investors' lawsuit. Overall, among companies we examine, cash settlements represented a 1.5% (171.5/11,236) aggregate recovery of investors' losses. Thorough analyses, starting with fraud models and ratios as red flags, may help prevent such devastating losses.

One of the major goals of risk management and assessment is the avoidance of a significant surprise or an outcome other than what is expected. While surprises do happen, it is a large surprise, whether good or bad, that leads to concern in risk analysis. Our analyses are based on assumptions in distributional properties of random variables. Our screening guidelines and follow-up procedures are applied to nineteen Chinese companies that had significant cases of fraud, eight of the most significant 21st Century company frauds, and four ongoing possible Chinese company frauds. Specifically, we apply an expanded set of risk focus measures including profitability and liquidity ratios, utilizing metrics in the balance sheet, income statement, and statement of cash flows. Frauds in companies that we analyze relate to IPOs and reverse mergers which encompass approximately $500 billion dollars in market capitalization destruction before being delisted, going bankruptcy, or suffering reputational damage.

* The authors are, respectively, Accounting Professor, Finance Professor, and Assistant Accounting Professor at University of Denver.

We show that the eleven screening red flags analyzed over fifty-two reporting years from 2006–2014 yielded fraud prediction rates from thirty-seven percent to ninety percent. These rates imply that coupled with more professional skepticism and analyses, screenings can alert preparers and users about red flags and motivate additional action to prevent investor losses. We note our analyses can assist not only a firm's internal governance, but also auditors, who are responsible to detect fraudulent activity that would result in a material misstatement in the financial statements. We believe our analyses may assist audit teams' fraud brainstorming discussions as part of their consideration of fraud per Statement on Auditing Standards (SAS) No. 99, Consideration of Fraud in a Financial Statement Audit. Another forensic accountant said: "All auditors must be forensic accountants in order to fulfill the responsibilities of SAS No. 99" (Yale, 2015). To facilitate this work, we outline recommendations for risk assessment follow-up procedures and ethical considerations.

Risk Management and Assessment Overview

Fraud risk management and assessment involves three main objectives: prevention, detection, and response. Companies are challenged with incorporating mechanisms to operationalize best practices to combat fraud. From building appropriate fraud assessment tools to managing prevention efforts, executives must commit to an ongoing process that continuously modifies risks, program designs, implementation systems, and evaluation techniques. In practice, firms employ codes of conduct, communication and training, fraud risk controls, and hotlines. Successful efforts enable management and Boards of Directors to prevent and detect misconduct such as improper revenue recognition, overstatement of assets, understatement of liabilities, misappropriation of assets, and payroll fraud. Our measures aim to assist with the risk analysis process.

We incorporate an approach similar to that of Coleman (2011), who argues that risk management is the art of using numbers and quantitative tools to actually manage risk. In assessing the overall risk of a company, Coleman focused on the variability of profits and losses (P&L) which provides a risk framework for levels of the firm from individual managers up through the board if calculated and reported on a consistent basis. He observed that managing risk requires being comfortable with randomness and thinking probabilistically, all of which require quantitative analysis for understanding and dealing with uncertainty, especially to inform, guide, and correct intuition. Risk managers, as well as auditors and forensic accountants, should be inquiring about the effectiveness of quantitative tools and analyses rather than relying solely on intuition (Coleman, 2011).

Consistent with Coleman's (2011) arguments that financial risk focuses on P&L and the variability of P&L, our methodology takes a probabilistic view to analyzing fraud. Randomness in P&L can be described by the distribution or density function. For managing risk, the major contribution of a P&L distribution is an understanding of how variable the P&L can be. Since risk measurement techniques require expertise and experience to use properly, managers, auditors, and forensic accountants have a responsibility to understand their complex businesses. Risk management techniques can try to put estimates around, but cannot properly represent, extreme or "black swan" surprise events. Risk managers and assessors have to learn to manage such uncertainty and avoid a false sense of security.

A common, well-known measure used to summarize the variability or the dispersion of the distribution is the standard deviation. For normal, well-behaved distributions, one standard deviation above and below the expected outcome indicates the result will be outside the range approximately thirty-two percent of the time. Two standard deviations above and below the expected outcome indicates the result will be outside the range approximately five percent of the time. If the standard deviation of the distribution is known, then management, auditors, and forensic accountants can predict the range of the outcomes with the best and worst possible values for both sixty-eight percent and ninety-five percent confidence ranges. Knowing the end points of these ranges shows how good or how bad the outcome can be. An outcome outside of the sixty-eight percent confidence range would be a surprise that could happen thirty-two of the time. An outcome outside of the ninety-five percent confidence range could happen five percent of the time, but these surprises can be outcomes that are much better, or much worse, than the expected outcome. Managers may have to change their plans and strategies if they desire an outcome close to the value of the expected outcome. The surprises that come from an outcome that is outside of the ninety-five percent confidence range may be so much larger or so much smaller than the expected outcome that the changes in plans and strategies may have to be dramatic.

Expansion of Risk Assessment Focus

We expand Colman's risk focus to include a liquidity focus with the variability of operating cash flows from the statement of cash flows and a solvency focus with the variability of cash from the balance sheet. All three major financial statements can contribute to risk management procedures.

Table I presents the formulas for our expanded risk measures that compare cash to accrual measures. See the Appendix for details of other fraud measures. The net income profitably focus is expanded to consider the quality of earnings ratio which is computed by dividing operating cash flows by net income. The operating cash flow liquidity focus is further expanded to consider the quality of revenues ratio which is computed by dividing the cash collected from customers by revenues. The cutoff for a good result for both ratios is one or better, assessing whether accountants' accrual measures are being converted into cash per a forensic accountant who recommended using both ratios with these cutoffs for fraudulent financial reporting detection (Schilit, 2010).

Table I: Expanded Risk Focus Measures

Measure	Formula
Net income profitability	$\frac{\text{Operating Cash Flows}}{\text{Net Income}}$
Operating cash flow liquidity	$\frac{\text{Cash collections from customers}}{\text{Revenues}}$

The cash solvency focus is expanded to consider the Sloan accrual ratio and the Altman bankruptcy model. The Sloan accrual ratio numerator is net income less free cash flows, which is computed as operating cash flows less capital expenditures. The Sloan denominator is average total assets and the cutoff is 0.10 where a result over this cutoff is a red flag (Robinson, 2007). The Altman bankruptcy model has the following overall cutoffs: Below 1.8 is a bankruptcy prediction; 1.8 to 3.0 is a possible bankruptcy prediction and over 3.0 is a non-bankruptcy prediction (Altman and Hotchkiss, 2005).

An additional focus for possible fraudulent financial reporting and earnings management, which can distort risk assessment procedures, is still needed. A 2012 survey of 170 CFOs of U.S. public companies indicated a twenty percent possibility of earnings management up to a possible ten percent distortion of earnings per share (Dichev, Graham, Harvey, and Rajgopal, 2013; Whitehouse, 2012). A McKinsey & Company report (2013) found that 100 small Chinese companies, mainly using reverse take-overs (RTO) to get listed on U.S. stock exchanges in 2005–2010, had then been delisted in 2011–2012 and destroyed over forty billion dollars in stock market value. Also, just eight major frauds of the 21st Century destroyed $490 billion in stock market value (Grove and Basilico, 2011). Thus, two fraudulent financial reporting prediction models are advocated for risk assessment. An "old fraud model" (Beneish, 1999) analyzed Securities and Exchange Commission (SEC) investigations of U.S. public companies from 1982-1992 and has a -1.99 cutoff where a larger result is a prediction for fraudulent financial reporting (smaller negative or positive numbers). A revised fraud model of Dechow, Ge, Larson, and Sloan (2007) analyzed SEC investigations from 1982–2006 and has a 1.00 cutoff where a larger result is a prediction for fraudulent financial reporting.

Risk Assessment Perspectives and Procedures

Risk assessment screening guidelines and follow-up procedures are now developed and applied. The results offer useful lessons and viable approaches to detect and deter international fraudulent financial reporting. These risk assessment guidelines and procedures, developed from practices by forensic accountants, financial analysts, and short sellers, hopefully, will become more widely used in the future to reduce fraudulent financial reporting.

Table II reports the nineteen Chinese IPO and RTO companies that had listed and then been delisted and/or suspended by U.S. and Hong Kong stock exchanges, the eight international companies representing major 21st Century frauds, and the four currently share-suspended Chinese Hong Kong IPO companies. Thirty-three financial reporting years over a 2006–2013 time period for these nineteen IPO/RTO companies were analyzed. Five of these companies were the most frequently cited ones by various short sellers (Bases et. al., 2011) so multiple, most recent reporting years before delisting were analyzed: the Longtop Financial Technologies IPO company (2007–2010) and four RTO companies: China Media Express (2008–2010), Harbin Electric (2006–2010), China-Biotics (2008–2010), and Deer Consumer Products (2008–2011). Another fourteen less frequently cited Chinese RTO companies were analyzed just in their last year before delisting to avoid analytical overload here. Eight reporting years for the eight major fraud companies of the 21st Century were analyzed, all in just their last year before the frauds were discovered and the companies suspended from trading. Eleven recent years were analyzed for the four Hong Kong IPO companies before their shares were suspended from trading in 2014: Kaisa Group Holdings (2009–2013), Tianhe Chemicals Group (2012–2013), Sihuan Pharmaceutical Holdings (2011–2013), and Superb Summit International Group (2014).

Table II: Fraud Companies in the Three Groups

19 Chinese IPO/RTO Companies	Eight Cos: 21st Century Frauds	Four Ongoing Possible Chinese Frauds
Longtop Financial Technologies	Enron	Kaisa Group Holdings
China Media Express	WorldCom	Tianhe Chemicals Group
Harbin Electric	Tyco	Sihuan Pharmaceutical Holdings
China-Biotics	Lehman Brothers	Superb Summit Internatl. Group
Deer Consumer Products	Health South	
Sino-Forest	Qwest	
China Shengda Technologies	Parmalat	
China Integrated Energy	Satyam	
China Electric Motor		
Orient Paper		
RINO International		
Douyuan Global Water		
United Travel Group		
New Oriental Education		
Gulf Resources		
China Education Alliance		
Wowjoint Holdings		
Keyuan Petrochemical		
Shen Zhou Mining		

The lowest forms of evidence are management representations and one of the highest forms is an independent expert's own analysis. Six well established ratios and models for fraud prediction include: Quality of earnings, quality of revenue, Sloan accruals measure, Altman Z-Score, Beneish Z-Score, and Dechow F-Score. These measures are advocated for anyone who needs to apply risk assessment screening guidelines, such as financial analysts, auditors, forensic accountants, risk managers, boards of directors, and government regulators. The five ratio inputs for one of these models (the Old Fraud Model) also have their own fraud prediction cutoffs so there are really eleven potential fraud screening measures. Although more detailed explanations are available (Grove and Clouse, 2014), refer to the Appendix for brief explanations of these six ratios and models with their fraud prediction cutoffs: Quality of Earnings (Schilit), Quality of Revenues (Schilit), Sloan Accrual Ratio, Altman Bankruptcy Model, Old Fraud Model (Beneish), and New Fraud Model (Dechow et.al., 2007). As expert witnesses in cases involving fraudulent financial reporting detection, forensic accountants can cite all these researchers who created and applied these fraud models and ratios in order to support their own forensic analyses (Grove 2007–2015).

We report eleven red flag ratios and models in Table III. The total actual and potential investment losses for the nineteen Chinese companies, the eight fraudulent 21st Century companies, and the four possible fraudulent companies was $540.2 billion or approximately $1/2 trillion. The key question is whether losses like these could be avoided had the risk assessment guidelines and procedures developed in this paper been applied to the analysis of these thirty-one companies. Overall 328 red flags out of 572 possibilities (52 x 11 red flags) or fifty-seven percent are reported.

Risk Assessment Screening Procedures

Five risk assessment screening procedures were developed from these eleven possible red flags. These procedures were based upon an approach developed by the Chief Investment Officer of John Malone's Private Investment Office for initial screening of potential investments and follow-up screening of actual investments. (John Malone's net worth is estimated at eight billion dollars.) The overall objective was to determine if cash was being generated from business operations and accumulated for business opportunities (Sierra, 2014):

1. Apply the New Fraud Model to ascertain if there are any predictions of fraudulent financial reporting. In Table III, the New Fraud Model showed red flags for fraud predictions ninety-four percent of the time over thirty-three reporting years leading up to the demise of the nineteen Chinese companies, sixty-three percent of the time in the last reporting year before fraud discovery for the eight fraudulent 21st Century companies, and 100% of the time over eleven years for the four possible Chinese fraud companies for an overall average of ninety percent.
2. If fraud predictions are generated by the New Fraud Model, then, apply the Old Fraud Model to check for consistency in predictions. The Old Fraud Model showed seventy-nine percent red flags or fraud predictions for the nineteen Chinese companies, thirty-eight percent for the eight international companies, and eighty-two percent for the four possible fraud companies for an overall average of seventy-three percent.
3. Calculate the Quality of Revenues ratio (Cash Collected/Revenues) since revenue recognition is the starting point for cash flow generation by business operations and is usually the number one manipulator in fraudulent financial statements. This ratio showed seventy-nine percent red flags for the nineteen Chinese companies, seventy-nine percent for the eight international companies, and eighty-two percent for the four possible fraud companies for an overall average of seventy-nine percent.

Table III: Red Flags Summary

			1			2			3			4	
			Chinese IPO/RTO Companies			**21st Century Frauds**			**Kaisa, Tianhe, Sihuan, and Superb**			**Whole Sample**	
Red Flag Summary		**Cut off**	**Totals**	**Percent**		**Totals**	**Percent**		**Totals**	**Percent**		**Totals**	**Percent**
New Fraud Model		> 1.00	31	94%		5	63%		11	100%		47	90%
Altman Bankruptcy		< 3.00	6	18%		7	88%		7	64%		20	39%
Old Fraud Model		>-1.99	26	79%		3	38%		9	82%		38	73%
	DSRI	> 1.03	16	48%		5	63%		7	64%		28	54%
	GMI	> 1.01	15	45%		5	63%		3	27%		23	45%
	AQI	> 1.04	15	45%		2	25%		6	55%		23	43%
	SGI	> 1.13	28	85%		6	75%		9	82%		43	83%
	TATA	> 0.02	12	36%		2	25%		6	55%		20	39%
Sloan Accrual		> 0.10	13	39%		2	25%		4	36%		19	37%
Quality of Earnings		< 1.00	14	42%		3	38%		9	82%		26	50%
Quality of Revenues		< 1.00	26	79%		6	75%		9	82%		41	79%
Total Red Flags			202			46			80			328	
Number of Financial Reports			33			8			11			52	
Multiplied by Eleven Possibilities			363			88			121			572	
Percent Red flags			56%			52%			66%			57%	
Investment Losses			$16.73			$490.00			$33.47			$540.2	
(in U.S. Billions)													
Number of Companies			19			8			4			31	

Note: Table III reports eleven screening red flags applied to fifty-two reporting years from 2006–2014 for thirty-one companies. Cut offs refer to the benchmark at which an outcome represents a red flag. For instance, an outcome greater than one based on the New Fraud Model indicates a red flag. The Totals and Percent column show the number of red flags indicated by each screening for the three types of companies explored: Chinese IPOs/RTOs (1), 21st Century Frauds (2), Possible Ongoing Frauds (3), and Whole Sample (4). As an example for Column 1, the New Fraud Model predicts thirty-one instances of fraud or fraud with ninety-four percent accuracy.

4. Calculate the Quality of Earnings ratio (Operating Cash Flows/Earnings) to determine if cash is being generated from business operations. This ratio showed forty-two percent red flags for the nineteen Chinese companies, thirty-eight percent for the eight international companies, and eighty-two percent for the four possible fraud companies for an overall average of fifty percent.

5. If there are red flags for quality of revenue, expand the revenue analysis with the calculation of both the Sales Growth Index (SGI) and the Days Sales Receivable Index (DSRI) from the Old Fraud Model. Both indexes compare the current year to the prior year. Per a public company Chief Financial Officer (CFO) who dealt with Wall Street on quarterly conference calls for over ten years: "Wall Street pays for two things: top line (sales) growth and operating leverage to get the top-line growth to the bottom line" (Coburn, 2015). The SGI ratio showed eighty-five percent red flags for the nineteen Chinese companies, seventy-five percent for the eight international companies, and eighty-two percent for the four possible fraud companies for an overall average of eighty-three percent. The DSRI ratio showed forty-eight percent red flags for the nineteen Chinese companies, sixty-three percent for the eight international companies, and sixty-four percent for the four possible fraud companies for an overall average of fifty-four percent.

For a summary of Table III, when these eleven screening red flags were applied over the fifty-two reporting years from 2006–2014 for these thirty-one companies, the overall fraud prediction was fifty-seven percent, showing 328 red flags out of 572 possibilities (52 x 11 red flags). Also, overall fraud prediction for the six key screening models and ratios, New Fraud Model, Old Fraud Model, Quality of Revenues, Quality of Earnings, Sales Growth Index, and Days Sales Receivable Index, respectively, were 90% (47/52), 73% (38/52), 79% (41/52), 50% (26/52), 83% (43/52) and 54% (28/52). When there are so many red flags for fraud prediction, professional skepticism and analysis can be expanded with such specific screening red flags providing guidance for follow-up procedures.

Risk Assessment Follow-up Procedures

Seven risk assessment follow-up procedures were developed from the prior five due diligence screening guidelines. These seven procedures rely heavily on the work of various short sellers and financial analysts who blew the whistle on many of these Chinese IPO and RTO company frauds (Bases et. al., 2011) and on many of these major frauds of the 21st Century (Grove and Basilico, 2011). These procedures have also been applied as forensic analysis to several of these delisted Chinese IPO and RTO companies (Grove and Clouse, 2014). These follow-up procedures were then applied to the four currently share-suspended Chinese Hong Kong IPO companies, Kaisa Group Holdings, Tianhe Chemicals Group, Sihuan Pharmaceutical Holdings, and Superb Summit International Group.

1. Competitive Analyses

Andrew Left, a short seller, commented: "Do Longtop's margins truly pass the smell test in cost-competitive China? Longtop's margins are far in excess of competitors" (Left, 2011). Table IV reflects a comparison of Longtop's performance in its 2007 IPO year with the average of its ten largest public competitors listed on Chinese stock exchanges.

Table IV

Measure	2007 IPO Year	Average of ten largest public competitors on Chinese Exchanges
Profit margin	18.6%	3.1%
Return on stockholders' equity	14.7%	1.5%
Price earnings ratio	92.9	48.5
Price revenue ratio	17.3	3.0

Also, Longtop showed profit margins in 2008–2010 before it was delisted of six percent, forty-one percent, and thirty-five percent, respectively (Grove and Victoravich, 2014).

Another short seller, John Hempton, asked how the simple business model of China Media Express, an RTO company, could earn thirty-one million dollars on fifty-seven million dollars in revenue for the third quarter of 2010. He called it, "the fattest margin and fastest growth media company I have ever seen" (Weinschenk, 2011). Andrew Left explicitly called China Media Express a "phantom company." While digging into industry reports on mass transit advertising in China, he found no references to China Media Express and articles that discussed industry competitors did not include China Media Express, even though the company claimed double the revenue per television screen as its competitors (Nachman, 2011).

2. Comparisons of Financial Report Filings with Different Entities

For various Chinese IPO/RTO companies, large discrepancies were found by comparing financial reports filed with the Chinese State Administration for Industry and Commerce (SAIC) to financial reports filed with the U.S. Securities and Exchange Commission (SEC). Such warning signs have become red flags for potential fraud by Chinese companies. For example, Left (2011) noted the following large differences for China-Biotics, Longtop Financial, and Harbin Electric. Two more short sellers, Carson Block (Bases et.al., 2011) and Alfred Little (2011) noted the following large differences for China Media Express and Deer Consumer Products, respectively. Anonymous Analytics (2014) noted a large difference in Tianhe Chemicals revenues. All the following differences and discrepancies were just too large to be caused by different reporting standards since Chinese generally accepted accounting principles (GAAP) and U.S. GAAP typically differ by only one percent to three percent:

	SAIC	SEC	SEC/SAIC Discrepancy
China-Biotics-2008:			
Cash	$ 100,000	$ 64,300,000	643 x
Accounts Receivable	1,000,000	13,200,000	13 x
Revenues	500,000	42,300,000	85 x
Gross Profits	200,000	30,000,000	150 x
Net Income	(1,200,000)	17,500,000	>17 x
China Media Express:			
Revenues-2009	17,000,000	95,900,000	6 x
Cash-2009	141,000	57,000,000	404 x
Cash-2010	10,000,000	170,000,000	17 x
Longtop Financial:			
Cash-2010	50,000,000	332,000,000	7 x
Harbin Electric:			
Net Income-2009	Net Loss	20,000,000	>20 x
Net Income-2010	Net Loss	77,000,000	>77 x
Deer Consumer Products:			
Land Purchase	11,300,000	23,200,000	2 x
Tianhe Chemicals			
Revenues-2012	106,000,000	684,000,000	6.5 x

For various U.S. 21st Century fraud companies, a similar strategy compared GAAP income tax rates reported to the SEC versus cash income tax rates computed from cash actually paid on U.S. Internal Revenue Service (IRS) income tax reports. For example, two of the largest 21st Century frauds, Enron, and WorldCom, both reported about thirty percent GAAP income tax rates to the SEC versus about four percent cash income tax rates from cash paid on IRS reports. Such discrepancies represented a 7.5 magnitude (Grove and Basilico, 2011).

A Muddy Waters short seller research report by Carson Block on Superb Summit was cited by various sources (Bhattacharya, 2014; Kumar and Roantree, 2014; Value Walk, 2014). A Muddy Waters Research (2015) investigative team for Superb Summit concluded that the following company acquisitions were misleading and/or false and found the following discrepancies (in millions of U.S. dollars), comparing SAIC to Hong Kong stock exchange filings, where Superb Summit had its IPO:

	SAIC	Hong Kong	Hong Kong/SAIC Discrepancy
Superb Summit:			
Coal Company Acquired	0	.2	> .2 x
Total Sales-2012	.1	18	> 18 x
Total Sales-2013	2	116	58 x
Energy Company Acquired	1	78	78 x

Thus, Superb Summit had similar magnitudes of reporting discrepancies as the previously cited Chinese IPO and RTO companies.

A Tianhe Chemicals report by a short seller, Anonymous Analytics, found that "SAIC filings and third-party documents show that Tianhe generates a fraction of the revenues and profits it reports. We present evidence that Tianhe does not pay the taxes it claims, and therefore could not have generated the profits it claims." In 2012, Tianhe's true revenue was eighty-five percent less than it reported and its net income was almost 100% less. Similar overstatements were made for 2011. Additionally, Tianhe's revenues were reported as $684 million for 2012 in its IPO prospectus but Chinese government filings showed only $106 million (AP, 2015).

3. Additional Revenue Work

The Quality of Revenues red flag ratio occurred seventy-nine percent of the time for these nineteen Chinese IPO and RTO companies and seventy-five percent of the time for these eight major fraud companies of the 21st Century. Various short sellers had flagged "channel stuffing" and "massaged revenue recognition" practices with corresponding receivables which were not yet billed and, thus, not yet collected, if ever (Durden, 2011).

A related red flag for expanding revenue work was the Sales Growth Index (SGI) which occurred eighty-five percent of the time for these nineteen Chinese IPO and RTO companies and seventy-five percent of the time for these eight major fraud companies. A second related red flag was the Days Sales in Receivable Index (DSRI) which occurred forty-eight percent of the time for these Chinese companies and sixty three percent of the time for these eight fraud companies as it is difficult to collect either pre-billed or phony revenues. A third related red flag was the Quality of Earnings which compares operating cash flows to net income. This ratio flagged reporting problems forty-two percent of the time for these nineteen Chinese companies and thirty-eight percent of the time for these eight fraud companies. These red flags show the difficulty in generating operating cash flows from either pre-billed or phony revenues

Accordingly, financial analysts have expanded their work concerning the existence of customers and corresponding revenues, accounts receivable, and cash inflows. For example, a Chinese financial analyst concluded that Sino-Forest (another of the nineteen Chinese IPO/RTO companies) claimed that its largest customer accounted for $325 million or seventeen percent of its 2010 revenues. She said this was not credible per an industry analysis. For Superb Summit, substantially all of its 2012 and 2013 revenues appeared to be attributed to sales of coal and related products from an acquisition in a company that was completely false (Kumar and Roantree, 2014). Tianhe's 2014 IPO filing disclosed that one principal customer, Shanghai Xidatong International Trading Company (SXITC), had accounted for approximately $100 million revenue in 2012 and 2013, but government data showed SXITC's own annual revenues in 2012 as only six million dollars and a net worth of a negative $900,000 (AP, 2015). Tianhe claimed its 2014 profitability was derived from superior operating margins of over sixty percent. By comparison, all

Tianhe's competitors report operating margins well below thirty percent per an Anonymous Analytics report (AA, 2014).

4. Additional Cash Work

Since various short sellers were questioning why many of these Chinese RTO companies had such a large amount and percentage of cash for their business operations, cash as a percentage of total assets was calculated for three ongoing, possible Chinese fraud companies in 2013, their last annual report year to date: Kaisa 7.7%, Tianhe 13.8%, and Sihuan 15.1% for an average of 12.2%, compared to the nineteen Chinese RTO companies' average of 34.5%. However, after Kaisa reported $1.383 billion of cash on June 30, 2014, it reported only $306 million of cash on March 1, 2015 (Yeoh, 2015). So, what happened to $1.077 billion of cash in just eight months? This is a huge red flag, similar to missing cash of over one billion dollars for both Parmalat (Europe's Enron) and Satyam (Asia's Enron), as cash was overstated in their last reported financial statements before these frauds were discovered.

Red flags for either missing cash or possible fraudulent cash would suggest applying the Altman Bankruptcy Model. The results for the three Chinese companies in their public reporting years before share trading suspensions were as follows:

- Kaisa (2009–2013): 1.13, 1.96, 2.72, 1.67, and 1.73—all bankruptcy predictions, except 2011 which was a possible bankruptcy prediction
- Tianhe (2012–2013): 2.41 and 2.40—both possible bankruptcy predictions
- Sihuan (2011–2013): 3.94, 3.86, and 7.66—no bankruptcy predictions

5. Site Visits

The first site visit that led to the detection of fraudulent financial reporting occurred in 1937. An audit associate found that a client's warehouse, which purported to have a nineteen million dollars inventory ($285 million in current dollars), was an empty lot. For this investigative work, he was fired by the Big 8 audit firm but, then, had to be rehired when proven correct! This fraud led to a change in auditing procedures where auditors had to actually inspect inventory to verify its existence (Fox, 2012).

Further investigations of possible fraudulent financial reporting were related to site visits of business operations and customers disclosed by these Chinese RTO companies. For example, a short-seller, The Financial Investigator, posted a video that it claimed was a tour of the China Media Express offices. The video featured sleeping employees, empty offices, and a business that was not the growth machine that China Media Express claimed (Bases et. al., 2011).

The Sino-Forest forestry business model was to operate through a series of authorized intermediaries or timber agents who would buy lumber, deliver them to a chipping facility, collect the woodchips, and sell them to an end user, and then pay Sino-Forest a cut of end profits for assuming risk for the whole operation. The Muddy Waters investigative team found that the timber agents that sold $2.9 billion to Sino-Forest generally operated out of apartments while purportedly doing annual revenue of hundreds of millions. Sino-Forest had signed a one billion dollars master contract with a forestry development company. The local governmental forest bureau had never heard of this company and the address of another timber agent, trading partner was in a fishing village (Weisenthal, 2011).

For Superb Summit, the Muddy Waters investigative team found that the proclaimed purchase of a technology company for seventy-eight million dollars was for a tiny, obscure chemical engineering consulting business with few assets and only a single engineer, its founder. The Tianhe AA report (2014) stated that "site visits show that most of Tianhe's purported customers in one of its two major product lines are related parties that share offices and overlapping management, which border on being non-existent" (AA, 2014).

6. Corporate Governance

Weak corporate governance often contributes to weak risk management and assessment which may facilitate fraudulent financial reporting. For example, the tipping point for the financial crisis was generally acknowledged to be the Fall, 2008 bankruptcy of Lehman Brothers. Risk management was very weak at Lehman Brothers as indicated by its ineffective risk management committee (Grove and Patelli, 2013). Lehman Brothers' risk committee only ever had two meetings, one in 2006 and one in 2007 before the company went bankrupt in 2008. The lack of Board expertise and competence was noteworthy with Lehman Brothers' risk management committee.

Based upon empirical corporate governance research (Allemand, 2013; Grove et.al., 2011), the following key variables were found to have a significant, negative impact on risk taking and financial performance and possible fraudulent financial reporting, as noted for Longtop Financial Technologies and Deer Consumer Products. Deer had the Chief Executive Officer (CEO) duality problem where the CEO was also the Chairman of the Board of Directors (COB). Longtop had staggered board elections so the entire board could not be removed at the same time. Deer had one older director who was sixty-six years old. Longtop had a bias toward short-term compensation mix (cash bonuses and stock options versus long-term stock awards and restricted stock) as the COB gave away eighty million dollars in stock to employees, claiming that money was just not important to him! Concerning lack of independent boards, Longtop's board had three of six (fifty percent) non-independent directors who were the COB, the CEO, and a Business Division director. Deer had two of five (forty percent) non-independent directors who were the CEO and CFO. Thus, overall corporate governance appeared to be weak at both companies with many problems indicated by these key research variables.

For most of Sino-Forest's public years, Ernst & Young (E&Y) Canada had been its auditors, which related to another problem of poor corporate governance, as former Canadian E&Y partners became members of Sino-Forest's Board of Directors. Per Carson Block, a short seller, a favorite strategy of Chinese RTO fraudulent companies has been to gain respectability by putting Westerners without significant knowledge of China's politics, industries, or business culture into management and Board positions.

At the time of its IPO, Kaisa listed six executive directors, who all had top management positions in Kaisa, and three independent non-executive directors. Thus, there was majority Board control by insiders (six of the nine directors). Also, the Kaisa company chairman was the chairman of three of the four Kaisa board committees with the exception of the audit committee. His brother was the vice chairman of the general board of directors. These two brothers and a third brother had formed a Family Trust which owned forty-nine percent of Kaisa. The Kaisa board only had two meetings in 2009, the IPO year, and the only two board members who attended both meetings were the two brothers! Kaisa reported that there were no audit committee meetings in 2009 because it was the company's IPO year. Also, the Board has staggered reelections for one-third of the directors each year so the entire Kaisa board could not be voted out in one year.

7. Ethics

Unethical behavior (even lying) occurred in press releases and other disclosures by various fraudulent Chinese RTO companies. There was a 2010 government investigation into a judicial corruption case where the Kaisa chairman/co-founder confessed to paying a $130,000 bribe to a judge. The judge then confessed to receiving this bribe, which allowed Kaisa to take over a business complex in a large southern China city. The judge is now serving a life sentence in jail but the Kaisa chairman escaped punishment. A government news agency described this business deal as "a miscarriage of justice by a manipulated judiciary" (Barboza, 2015). In late 2014, Kaisa's chairman was again being questioned about both this 2010 corruption case and another governmental fraud investigation. In December, 2014, this Kaisa company chairman resigned, "due to health reasons." The Kaisa vice-chairman and the Kaisa CFO also resigned in December (White, 2015). By March, 2015, 170 senior Kaisa managers had resigned.

Concerning a recent ethical case, Volkswagen appears to have rigged its sales growth and profits by designing software to defeat diesel engine emission requirements to "make its performance numbers." After Volkswagen admitted to installing "defeat devices" in more than eleven million diesel engine vehicles worldwide in late 2015, Volkswagen lost 1/3 of its market cap in one week and recalled 8.3 million diesel vehicles in Europe. Up to 350 lawsuits have already been filed in the United States where 500,000 of these vehicles were sold.

Volkswagen also had corporate governance issues. The Volkswagen Board of Directors has major independence problems as nine of the twenty Board members (forty-five percent) are or have been Volkswagen executive managers (Minow, 2015). Volkswagen, Germany's largest company, employs nearly 280,000 people in Germany, mainly in the state of Lower Saxony where Volkswagen has its headquarters. The state of Lower Saxony owns twenty percent of Volkswagen common stock. Thus, if the union and local government board members, all with strong, possibly dependent, economic links to Volkswagen, are included, there are now fourteen of the twenty members (seventy percent) who could be non-independent. Furthermore, Volkswagen family members control a majority of voting shares and one family member had been the COB for over twenty years until early 2015. A financial press writer has commented: "Make Leaders Lead—wouldn't it be nice if executives acted like leaders and accepted responsibility for the actions of their companies and their employees?" (Morgenson, 2012).

Summary and Conclusions

There were numerous red flags, representing risk assessment screening guidelines and indicating the need for follow-up investigative procedures, which apparently were lacking in these fraud cases. Using the fraud models and ratios advocated in this paper, financial statement users could increase their understanding of risk and better meet their fiduciary responsibilities as auditors, forensic accountants, financial analysts, investment bankers, investment managers, short sellers, and Board members. It is especially important for Boards of Directors to pay attention to the fraud predictions by these fraud models and ratios as directors should not be in a position where they are surprised by fraud within an organization (Morgenson, 2013). All the results in this paper suggest that there are useful red flag indicators for possible fraudulent financial reporting, as indicated by both risk assessment guidelines and follow-up procedures. Additional procedures by various financial analysts and short sellers, who detected fraud in Chinese companies, have been discussed in the following sources: Bases et.al., 2011; Bishop, 2011; Fox, 2012; Left, 2011; Norris, 2011; Sandler, 2013.

We employ increased risk assessments using international companies that demonstrate a need for increased utilization for more oversight of company performance. Considering China's recent economic and stock market problems, Jim Chanos, the billionaire short-seller, commented that the Chinese government's reaction to its stock market volatility, panic responses from investors, and recent currency devaluation have all given investors pause: "Like many other bad ideas, the Chinese have finally adopted the Western practice of discouraging financial critics and banning short-selling when markets turn down, It has never worked here and does not appear to be working there, either" (Wong et. al., 2015). We encourage the use of the fraud models and ratios to provide such clues as starting points for the risk assessment screening guidelines and detailed follow-up procedures developed here.

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Appendix: Red Flag Ratios and Models

Six various models and ratios have been used to develop a red flag approach in screening for and identifying fraudulent financial reporting and earnings management in publicly held companies in addition to traditional ratios. The models are available from the authors in an Excel file.

1. **Quality of Earnings**

The quality of earnings ratio is a quick and simple way to judge the quality of companies reported net income. The ratio is operating cash flow for the period divided by net income for the period. The red flag benchmark is a ratio of less than 1.0 (Schilit, 2003). Also, large fluctuations in this ratio over time may be indicative of financial reporting problems, i.e., Enron's quality of earnings ratios were 4.9, 1.4, and 2.3 over its last three years of operation. In its last year of operation, Enron forced its electricity customers to prepay to receive any electricity which dramatically increased its operating cash flows and quality of earnings ratio. Quality of earnings is also meant to measure whether a company is artificially inflating earnings, possibly to cover up operating problems. This ratio may indicate that a company has earnings which are not actually being converted into operating cash. Methods for inflating earnings (but not operating cash flows) include early booking of revenue, recognizing phony revenues, or booking one-time gains on sales of assets.

2. **Quality of Revenues**

The quality of revenues ratio is similar to the quality of earnings, except that the emphasis is on cash relative to sales rather than cash relative to net income. It is the ratio of cash collected from customers (revenues plus or minus the change in accounts receivable) to the company's revenue. Similar to the quality of earnings ratio, the red flag benchmark is a ratio of less than 1.0 (Schilit, 2003). For example, Enron's quality of revenues went down from 0.98 to 0.92 in its last year of operation. Since manipulation of revenue recognition is a common method for covering up poor results, this simple metric can help uncover schemes used to inflate revenues without the corresponding cash collection. Common methods include extending increased credit terms to spur revenues but with slow collections, shifting future revenues into the current period, or booking asset sales as revenue.

3. **Sloan Accrual Measure**

The Sloan accrual measure (Robinson, 2007) is based on the analysis of accrual components of earnings. It is calculated as follows: net income less free cash flows (operating cash flow minus capital expenditures) divided by average total assets. The red flag benchmark is a ratio of more than 0.10. For example, Sloan calculated that JetBlue had a ratio of 0.50 and his employer, Barclays Global Investors, shorted the stock and made over twelve percent in less than one year. This ratio is used to help determine the quality of a company's earnings based on the amount of accruals included in income. If a large portion of a company's earnings are based more on accruals, rather than operating and free cash flows, then, it is likely to have a negative impact on future stock price since the income is not coming from the company's actual operations. Since many of the accrual components of net income are subjective, managers can manipulate earnings to make the company appear more profitable. Thus, the Sloan accrual measure is used to help determine the sustainability of a company's earnings.

4. **Altman Z-Score**

The Altman (2005) Z-Score is a multivariate statistical formula used to forecast the probability a company will enter bankruptcy within the next two years. The model contains five ratios which are listed below with their coefficients, based on Altman's research. The model was originally developed in 1968 for evaluating the bankruptcy risk of traditional public firms, such as manufacturing, energy, and retail, but it can also be applied to non-traditional and service public firms, such as software, consulting, and banking, as well as private firms. All three versions of the model are available on the Bloomberg software subscription package. The red flag bankruptcy prediction of the original model is a Z-Score of less than 1.8, with a score between 1.8 and 3.0 indicating possible bankruptcy problems. For example, Altman predicted that General Motors would "absolutely" seek bankruptcy protection and they come up very seriously in the Z-Score test into the bankrupt zone after a thirty- to sixty-day reorganization.

5. Z-Score (Beneish Old Fraud Model)

Beneish (1999) developed a statistical model used to detect financial statement fraud and earnings management through a variety of metrics. There are five key ratios used in the model, which are the Sales Growth Index (SGI), Gross Margin Index (GMI), Asset Quality Index (AQI), Days Sales in Receivables Index (DSRI), and Total Assets to Total Accruals (TATA). Each of these measures with its model coefficient, based upon Beneish's research, is outlined below. There is also a constant value in the model of -4.840. The red flag benchmark is a Z-Score greater than a negative 1.99, i.e., a smaller negative number or a positive number indicates possible financial reporting problems. For example, Enron had a fraud Z-Score of a positive 0.045 in its last year. Also, this model is the only one with fraud guidelines for each of the model's five inputs as follows:

	Non-manipulator's mean index	**Manipulator's mean index**
DSRI (Days sale in A/R index)	1.031	1.465
GMI (Gross margin index)	1.014	1.193
AQI (Asset quality index)	1.039	1.254
SGI (Sales growth index)	1.134	1.607
TATA (Total accruals to total assets)	0.018	0.031

6. F-Score (Dechow New Fraud Model)

This F-Score fraud model (Dechow, Ge, Larson, and Sloan, 2007) can be used as a test for determining the likelihood of financial reporting manipulation. Similar to the other models and ratios, a fraudulent score for this model does not necessarily imply such manipulation but it serves as a red flag for further analysis. The model contains measures to identify problems in accruals, receivables, inventory, cash sales, earnings and stock issuances as discussed below with their coefficients. There is also a constant value of -6.753 in the model. The resulting predicted value (PV) is used in an exponential equation: e^{PV} / $1+e^{PV}$ to get a company fraud probability. This probability is divided by the unconditional (and constant) fraud probability of all the sample companies' financial years: 494 / (143,452 + 494) = 0.0034. The F-Score result is a fraud red flag if greater than 1.0. For example, the F-Score for Enron in its last year of operation was 1.85. This research is the more extensive of the two fraud models since it was based upon an examination of all Accounting and Auditing Enforcement Releases (AAERs) issued by the SEC from 1982–2005 while the older Beneish study was based only on AAERs issued from 1982–1992. The new fraud model was based on detecting 434 fraudulent reporting years out of 143,946 reporting years.