Rev Account Stud (2015) 20:1373–1406
DOI 10.1007/s11142-015-9326-y

Understanding investor perceptions of financial statement fraud and their use of red flags: evidence from the field

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Published online: 30 June 2015

Abstract We surveyed 194 experienced, nonprofessional investors to examine the relations between their perceptions of the frequency of financial reporting fraud, their use of financial statement information, the importance they place on conducting their own fraud risk assessments, and their use of fraud red flags. We find that investors' perceptions of the frequency of fraud and their use of financial statement information positively influence the importance they place on conducting their own fraud risk assessments. Investors who place importance on assessing fraud risk make greater use of fraud red flags to avoid fraudulent investments. Red flags commonly relied upon include SEC investigations, pending litigation, violations of debt covenants, and high management turnover. Investors rely less on company size and age, the need for external financing, and the use of a non-Big 4 auditor. We also find evidence of positive associations between the use of specific red flags and investors' portfolio returns.

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Keywords Financial statements · Fraud red flags · Fraud risk · Investors

JEL Classifications M40 · M41 · M48

1 Introduction

The decision making of nonprofessional investors matters to standard setters and investor protection groups. Congress and the Securities and Exchange Commission (SEC) have expressed their intent to protect nonprofessional investors from fraudulent financial reporting (Public Law [107-204] 2002; Cox 2005). Given the red flags that accompanied high-profile frauds including Enron, HealthSouth, and Bernard L. Madoff Investment Securities LLC, policymakers are interested in ways investors can use red flags to protect themselves from fraudulent financial reporting (Hubbard 2002; Brazel et al. 2009; Markopolos 2010). Former SEC Chairperson Mary Schapiro has stated that changes need to be made "so investors can better understand the information they [receive] and to make clearer red flags that might sometimes signal a potential fraud" (Schapiro 2011). However, little is known about investors' perceptions regarding fraudulent financial reporting and whether and how they protect themselves from investing in fraudulent firms. The purposes of this study are to establish whether investors concern themselves with conducting fraud risk assessments and, if so, which information they use to do so. A greater understanding of investor decision making with respect to fraud can aid researchers, policymakers, and investor protection groups in achieving their goal of enhancing investor protection.[1]

We develop a framework in which we predict that investors who perceive fraud to be prevalent in the economy or who rely primarily on financial statement information in their investment decisions will place greater importance on conducting their own fraud risk assessments when considering an investment. We then test whether a belief in the importance of fraud risk assessments leads to greater use of fraud red flags to avoid potentially fraudulent investments.

To test our framework, we administered a survey to 194 experienced, nonprofessional investors. Participants were pre-screened to ensure they had traded individual company stocks within the prior 12 months. Our sample consists of a geographically diverse group of active investors from 38 states and the District of Columbia. We employ the survey method to examine investors' perceptions about the rate of fraud in the economy, measure their personal use of financial statement information, and determine the actions they take to avoid investing in fraudulent firms. A survey also allows us to study the relations between several investor attributes simultaneously and to provide important descriptive data for future research. We acknowledge that a limitation of the survey method is the ability to measure only associations. It is our hope, however, that our findings spur research employing multiple methods in the area of investor fraud protection.

[1] Our use of the term, "fraud," refers only to fraudulent financial reporting. We use the terms "fraud" and "fraudulent financial reporting" interchangeably. Similarly, our use of the term "investors" refers explicitly to nonprofessional investors. Future research can determine whether the findings of our study generalize to professional investors.

Consistent with our expectations, we find that both investors' perceptions of the prevalence of fraud in the economy and their use of financial statement information positively influence the importance they place on conducting fraud risk assessments. In turn, investors placing greater importance on fraud risk assessments report greater use of red flags in their investment decision making. While research describes the usefulness of red flags in identifying fraud (e.g., Beasley 1996; Brazel et al. 2009; Dechow et al. 2011), this study illuminates investors' use of these red flags.

Our study provides a better understanding of investors' use of information to avoid potentially fraudulent investments. We demonstrate that, in general, investors tend to focus on the following red flags: SEC investigations, pending litigation, violations of debt covenants, and high management turnover. In contrast, investors rely less on company size, company age, the need for external financing, and the use of a non-Big 4 auditor. More broadly, we find that investors, in general, tend to focus on red flags exhibited in the late stages of fraud. However, we observe that investors who deem fraud risk assessment as important tend to use both early- and late-stage red flags. Survey participants also provided their portfolio's rate of return over the previous 12 months. We present initial empirical evidence of positive associations between the use of specific red flags and investor returns. Nonprofessional investors who specifically target certain red flags (accruals in particular; early-stage red flags in general) achieve higher market returns.

Last, participants indicated their perceptions regarding the parties, beyond themselves, they believe are responsible for detecting fraud. They report a stronger reliance on analysts, regulators, and external auditors to detect and report fraud and a lesser reliance on low/mid-level employees, upper management, the media, and short sellers to uncover fraud. Interestingly, these perceptions contradict recent evidence suggesting that the media, employees, analysts, and short sellers are all more likely than auditors and the SEC to detect fraud (Dyck et al. 2010). Indeed, Ljungqvist and Qian (2014) indicate that short sellers who have information about questionable corporate governance or accounting practices but who face short sale constraints make public their information in hopes of influencing other investors to trade in such a way that corrects an overvaluation. However, we find nonprofessional investors lack awareness of the valuable resource provided by short sellers in the area of fraud detection.[2] Our findings should encourage future research in this area. For example, why do investors rely more on analysts, who typically follow firms about which they have a favorable opinion, while relying less on short sellers who uncover and report information regarding potential mispricing (e.g., fraud red flags) to reduce the risk of their arbitrage (e.g., Ljungqvist and Qian 2014)? Answers to these questions could prove beneficial in the form of improved investor protection and increased market efficiency.

To our knowledge, we are the first researchers to examine whether investors deem fraud risk assessment as an important investing activity or to determine the

[2] Table 3, Panel A in Ljungqvist and Qian (2014) provides a breakdown of the information provided by these short sellers, which, in some cases, could indicate fraudulent financial reporting. Our results suggest that nonprofessional investors are unlikely to look to the information provided by short sellers as informative about potential fraud red flags. Consequently, this could also prove detrimental to short sellers who make public their private information to reduce arbitrage risk, as the market's failure to trade in a timely manner on this information could increase short sellers' risk exposure.

specific actions investors take to avoid potentially fraudulent investments. From a public policy standpoint, we provide a profile of the type of investor who is *not* likely to include fraud risk assessments and the use of red flags as part of his investment decisions. Regulators, whose objective is to protect individual investors (e.g., SEC, FINRA), can begin to target this group of investors to educate them on fraud risk and ways to minimize losses due to fraud. Our results also demonstrate that investors, in general, are less likely to use early-stage red flags, which are likely more beneficial but are harder to decipher than late-stage red flags (Dichev et al. 2013). Tests of our framework indicate that investors relying directly on financial statements deem fraud risk assessment as important but tend not to use red flags. As such, our results support calls to make early- and late-stage red flags more transparent for investors (Schapiro 2011). For example, regulator or investor websites could accumulate and disclose red flag measures (e.g., accrual levels, auditor changes) to assist investors in identifying companies that are beginning to exhibit multiple early-stage red flags.[3]

Despite numerous high-profile frauds in recent years and the high cost of fraud to market participants, investor decision making regarding fraud has largely gone unexamined. Our study provides rich descriptive data and initial empirical evidence of associations between key fraud-related variables. Additionally, our findings provide a foundation for future research and policy initiatives in the important area of investor fraud protection (e.g., Schapiro 2011).

2 Background and development of hypotheses

Nonprofessional investors are a significant component of the equity market and are susceptible to significant losses from fraud (e.g., Bogle 2005; NASAA 2006; Elliott et al. 2008). According to the North American Securities Administration Association, investors lose $40 billion annually due to securities fraud (NASAA 2006). Despite nonprofessional investors' exposure to fraud, little research has examined whether and how these investors evaluate fraud risk when making investment decisions.

Whether investors deem fraud risk assessment as an important part of their investment decision making is an open empirical question. As noted by Mercer (2004), investors rely, in part, on the level of external assurance (e.g., audit opinions) provided for firm disclosures in determining the reliability of those disclosures. Moreover, prior research indicates that investors have higher expectations than auditors regarding auditors' responsibility for detecting fraud (e.g., McEnroe and Martens 2001). This research suggests that investors may see little need to conduct their own fraud risk assessments because they place the

[3] The accumulation and disclosure of early- and late-stage red flag data by a regulator resembles actions that are underway at the Public Company Accounting Oversight Board (PCAOB) in relation to measuring audit quality. The PCAOB notes that the "visibility of audit quality to investors is limited." As such, it is developing a set of audit quality indicators that will include early-stage (e.g., partner workload) and late-stage (e.g., financial statement restatement) measures of audit quality for a given company's year-end audit. The intent is to collect data in relation to these indicators and make them available to a variety of capital market participants (http://pcaobus.org/News/Events/Documents/1115162013_SAG/11142013_AQI.pdf, http://pcaobus.org/News/Events/Documents/0624252014_SAG_Meeting/06242014_AQI.pdf).

responsibility of detecting fraud on others. Given recent high-profile frauds, however, investors may now experience an increased need to include a fraud risk assessment as part of their investment decision making.

Prior research has documented certain red flags that indicate an increased likelihood of fraud (e.g., Lee et al. 1999; Brazel et al. 2009; Dechow et al. 2011). However, even in cases where investors deem fraud risk assessment as important, it is unknown whether they consider these red flags when investing. Below we present a framework that examines the characteristics of investors who are likely to perform their own fraud risk assessments and, in turn, use fraud red flags when investing. Before presenting our framework and formal hypotheses, however, we present an overview of empirically documented fraud red flags.

2.1 Fraud red flags

Prior research identifies three factors that are typically present when fraud occurs. These factors, called the "fraud triangle," are incentives, opportunities, and attitudes (Bell and Carcello 2000; Rezaee 2005; Hogan et al. 2008; Trompeter et al. 2013). Research also identifies red flags related to each of these factors that can indicate an increased likelihood of fraud. Incentive-related red flags include inducements from capital markets (e.g., earnings expectations) and management compensation schemes that result in a perceived benefit from committing fraud. For example, several studies find a link between the level of management's equity-based compensation and the likelihood of accounting irregularities (Efendi et al. 2007; see Armstrong et al. (2013) for a review). Opportunity-related red flags include weak corporate governance and other working conditions that create circumstances that allow management to commit fraud. Farber (2005) documents that firms with fewer independent board members, fewer audit committee meetings, fewer financial experts on the audit committee, a non-Big 4 auditor, and CEOs who are also the chairmen of the board are more likely to commit fraud. Attitude-related red flags reveal management's propensity to rationalize fraud. If a subset of management has such a propensity, executives who do not share this attitude are likely to resign (Feng et al. 2011). Thus high manager turnover may be viewed as a potential fraud red flag.[4]

The fraud literature has also identified red flags that can be gleaned from a firm's financial statements. For example, Lee et al. (1999) find that a large difference between earnings and cash flows from operations can indicate fraud. If earnings are fraudulent, there will be no corresponding cash inflow. In summary, red flag data related to fraud can be obtained from a variety of sources including a company's 10-K filing (e.g., total accruals), 8-K filing (e.g., auditor or management turnover), other SEC filings (e.g., board of director composition and equity-based compensation disclosures), and the popular press (e.g., an SEC inquiry). If investors

[4] For example, during the 7-year fraud at HealthSouth, the company employed five different CFOs (http://investor.healthsouth.com/secfiling.cfm?filingID=950172-04-1357). Management turnover, particularly CFO turnover, could also be related to the incentives of the CEO to pressure subordinates to manage earnings. Indeed, Feng et al. (2011) present findings that suggest that CFOs involved in material accounting manipulations are often succumbing to pressure from CEOs.

perceive fraud risk assessment as important, research has identified red flags they could use to assess the likelihood a firm is fraudulently reporting.

2.2 Framework of investors' use of red flags

We propose a framework to examine the characteristics of investors who are likely to deem fraud risk assessment as important and, in turn, use fraud red flags in their investment decisions. Specifically, we examine the relations between investors' perceptions of the prevalence of fraud in the economy, their reliance on financial statement information, their beliefs about the importance of conducting fraud risk assessments, and their use of fraud red flags. We expect that investors who perceive a higher rate of fraudulent reporting in the economy will place greater importance on conducting their own fraud risk assessments. Additionally, we predict that investors who primarily rely on financial statement information will place greater importance on conducting fraud risk assessments than investors who primarily rely on other information sources. In turn, we expect a positive relation between the importance placed on assessing fraud risk and the consideration of fraud red flags. Figure 1 provides an illustration of our framework. Below we discuss the individual components of the framework and develop hypotheses to test it.

The first component of our framework presents characteristics of investors who are most likely to place importance on conducting their own fraud risk assessments. First, when individuals perceive increased risk of monetary loss from some action (e.g., potential loss from investing in a fraudulent firm), they invest additional effort in activities to self-insure against that loss (Dionne and Eeckhoudt 1985; Briys and Schlesinger 1990; Jullien et al. 1999). Perceived risk is an antecedent to motivation in information processing (Chaiken et al. 1989). As such, a positive relation between investors' perceptions of the prevalence of fraud in the economy and the importance they place on conducting their own fraud risk assessments would be expected. However, research indicates that investors rely on auditors, regulators, and others to detect and report financial statement fraud (McEnroe and Martens 2001; Mercer 2004). This could suggest that investors deem fraud risk assessment to be a task better suited for other capital market players, regardless of investors' perceptions of the frequency of fraud. However, given recent high-profile frauds, some investors may deem the rate of fraud to be high enough to warrant their own analyses. For investors who do not perceive fraud to be prevalent, fraud risk assessment will not be important, as there is little motivation to assess the risk of a rare event.

Second, when making decisions, investors can choose from various sources of information including financial data that is provided directly by firm management, information prepared by professional advisors for investor consumption, advice from the media, macroeconomic data, and others (Elliott et al. 2008).[5] The direct use of financial statement information allows investors to perform their own direct

[5] We will use the term "reliance on financial statement information" to describe the relative reliance on financial statement information versus other information sources and data. In Sect. 3, we describe how, similar to Elliott et al. (2008), we develop a measure of investors' reliance on financial statement information relative to other information.

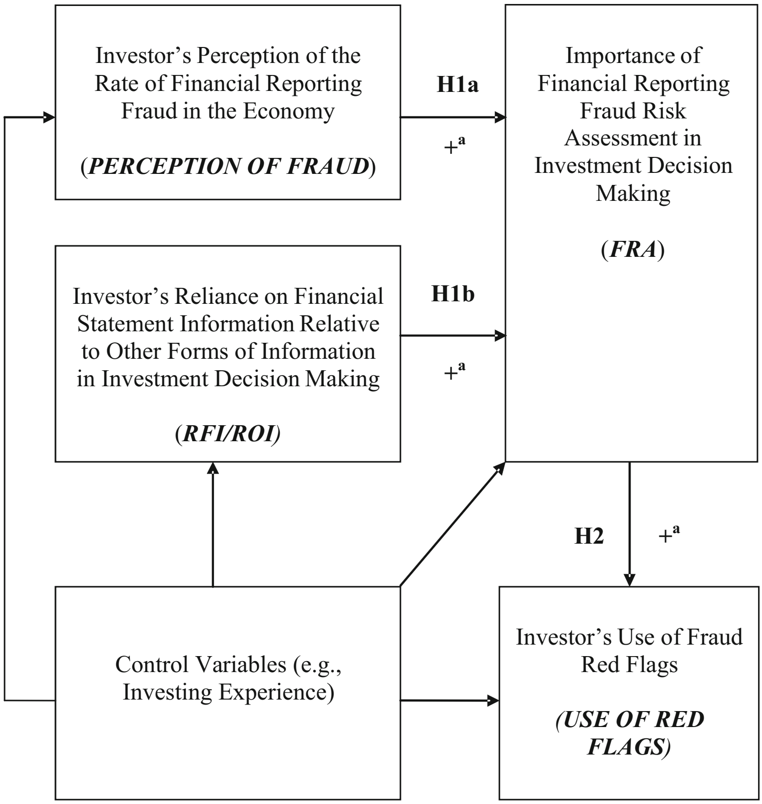

Fig. 1 Investor perceptions of financial statement fraud and their use of red flags. [a]H1a predicts that *FRA* increases as *PERCEPTION OF FRAUD* increases. H1b predicts that *FRA* increases as *RFI/ROI* increases. H2 predicts that *USE OF RED FLAGS* increases as *FRA* increases

analysis of a firm's operations to meet their specific investment needs (Hodge and Pronk 2006). Given the high-profile frauds of the past decade, investors who are savvy enough to read financial statements may seek to assess the likelihood of fraud as part of their financial statement analyses. On the other hand, investors who choose information from *secondary* sources may do so because they lack confidence in their own ability to comprehend and analyze complex accounting information found in a firm's financial statements (Hodge and Pronk 2006; Elliott et al. 2008). Investors who rely predominately on others to analyze or synthesize a firm's financial reporting may also be more likely to rely on those intermediaries (e.g., advisors, analysts) to assess the risk of financial reporting fraud.

In sum, we consider the effects of two investor characteristics—their perceived rate of fraud in the economy and their reliance on financial statement information—on the importance investors place on conducting fraud risk assessments. We predict that each of these characteristics will positively influence the importance investors place on conducting a fraud risk assessment as part of their investment decision making.

H1a: The importance investors place on conducting fraud risk assessments increases as their perception of the rate of fraud in the economy increases.

H1b: The importance investors place on conducting fraud risk assessments increases as their reliance on financial statement information increases.

While H1a and H1b describe the type of investors we expect to place importance on conducting fraud risk assessments, the manner in which these investors do so is an open empirical question. As noted above, research has identified red flags that can indicate fraud. This leads to the second component of our framework, investors' use of fraud red flags.

Logistically, it may be difficult for investors to use red flags, regardless of the importance they place on conducting fraud risk assessments. For example, nonfinancial data, which can be used to corroborate financial data (e.g., an increased number of retail outlets supports increased sales), is typically provided for the current year only (vs. comparative financial data) and is dispersed in paragraph form throughout the 10-K (Brazel et al. 2009). Also, red flag data may be disclosed in reports that some investors may not read (e.g., auditor change reported in an 8-K). Likewise, investors may not fully understand red flags that can indicate fraud. For example, while Lee et al. (1999) illustrate that large accruals are a fraud red flag, Hewitt (2009) finds that both professional analysts and nonprofessional investors fixate on earnings and have trouble separating cash flows from accruals in financial statements.

Thus it is not clear whether investors who perceive fraud risk assessment to be an important investment activity will necessarily use red flags when making investment decisions. Still, Elliott et al. (2008) highlight that experienced nonprofessional investors can use firm-provided financial information effectively. Moreover, research in psychology suggests that individuals who have both the motivation and the ability to process information will be more likely to conduct a controlled, systematic, and effortful analysis of the information (Petty and Cacioppo 1986; Chaiken et al. 1989). Above, we describe how investors who place importance on conducting their own fraud risk assessment are likely motivated (H1a) and have the ability (H1b) to perform their own fraud risk assessments. In turn, we expect the importance investors place on conducting their own fraud risk assessments will be positively associated with the extent to which they use red flags to determine the veracity of a firm's financial reporting. As such, we offer the following hypothesis:

H2: The importance of fraud risk assessment is positively associated with investor use of fraud red flags.

3 Method

We use the survey method to collect investors' perceptions of the rate of fraud in the economy, their personal use of financial statement information, the importance they place on fraud risk assessment, and the red flags they use when assessing the risk of financial reporting fraud. Given the paucity of research related to investors' consideration of fraud, the survey method allows us to examine multiple relations simultaneously. It also permits the collection and analysis of rich descriptive data that can serve as a starting point for future empirical research.

3.1 Sample

One hundred and ninety-four experienced, nonprofessional investors completed an online survey for this study. The Toluna Group (www.toluna-group.com) distributed the survey, titled "Survey on Investor Beliefs."[6] Questions in the survey included measures addressing both fraud- and nonfraud-related topics. The variety of measures collected allowed for both the primary purpose of our study to be concealed and the collection of a variety of investor attributes and information regarding investment decision making.

Toluna screened their database for participants who were actively trading individual shares of stock (vs. passively investing in mutual funds). We further screened participants by requiring that they answer "yes" to the following statement: "I have bought or sold individual company stock in the last 12 months." Toluna distributed the survey to 1178 participants. Thus the response rate is 16.5 %, which is comparatively high given the response rates of previous investor surveys.[7]

Study participants were from 38 states and the District of Columbia. Approximately 50 % of the participants were male. Seventy-two percent held a bachelor's degree or higher. Participants were, on average, between 40–49 years old and reported an average annual household income of $60,000–$90,000. Participants also reported an average of 6–10 years of investing experience.[8]

Our sample is consistent with descriptive data from household surveys of nonprofessional investors as reported by the Investment Company Institute (ICI

[6] The Toluna Group provides online research and survey technology solutions to market researchers, the media, corporations, and academicians. At the time of our study, Toluna maintained a global panel of 3.7 million active consumers, investors, and professionals. Toluna has been providing polling and survey data since 2000 and is the second largest company in its industry in terms of revenues. Its main competitors are Research Now, uSamp, and Survey Sampling International. For any particular data collection, a cross-section of the panel can be used or specific subgroups can be targeted. Participants in our survey were incentivized by Toluna's points reward system (the points awarded for completing a survey are determined in advance based on the length of the survey). Points are not awarded based on the reasonableness or accuracy of participants' responses. The survey was advertised to participants via our ambiguous title, "Survey on Investor Beliefs." The average Toluna participant completes eight surveys per year.

[7] For example, the response rate for Elliott et al. (2008) was approximately 3 %. Because not all individuals responded to our survey, we examined the potential for nonresponse bias. Previous research (Filion 1975; Wallace and Mellor 1988; Oppenheim 1992) finds that nonrespondents behave like late respondents. Thus Wallace and Mellor (1988) and Oppenheim (1992) recommend comparing data from late respondents to that of early respondents to assess this bias. Accordingly, we compared the responses from the first quartile of respondents to those in the last quartile. Results indicate no statistically significant differences for any of our hypothesized variables in Table 1 (including all underlying questions). This suggests that the responses for early and late respondents are similar and that nonresponse bias is not likely a concern (Wallace and Mellor 1988).

[8] Descriptive statistics (control variables) for our sample are presented in Table 2 and discussed in Sect. 4.

Table 1 Descriptive statistics—hypothesized variables

	Important (7,6,5)	Neutral (4)	Not important (3,2,1)	Response mean	H_0:Avg rating = **5.13**
Panel A[a]					
Financial information					
1. Mean reliance on financial information (*RFI*)	72.3	14.4	12.4	**5.13**	
2. Balance sheet	74.2	13.4	12.4	5.32	*
3. Cash flow statement	73.7	13.9	12.4	5.30	
4. Income statement	72.7	12.9	14.4	5.24	
5. Internal control effectiveness	62.4	21.1	16.5	5.01	
6. Statement of owners' equity	63.9	22.2	13.9	4.99	
7. Notes to financial statements	62.4	19.6	18.0	4.91	*
					H_0:Avg rating = 4.70
Other information					
8. Mean reliance on other information (*ROI*)	58.8	23.7	17.5	**4.70**	
9. Stock price	77.8	7.7	14.4	5.46	***
10. Advice from professionals	70.1	11.9	18.0	5.07	***
11. Company risk	63.9	18.6	17.5	4.98	**
12. Macroeconomic factors	58.2	21.6	20.1	4.75	
13. Nonfinancial information related to operations	50.0	22.2	27.8	4.40	**
14. Advice from media	45.9	19.1	35.1	4.17	***
15. Advice from nonprofessionals	41.2	21.1	37.6	4.03	***
Reliance on financial information relative to other information	More financial information > 1	Same = 1	More other information < 1	Response mean	
Panel B					
16. *RFI/ROI*[b]	60.3	10.8	28.9	1.12	

Table 1 continued

Perception of rate of fraudulent financial reporting	Majority > 50 % (11–7)	Half 50 % (6)	Minority < 50 % (5–1)	Response mean
17. *PERCEPTION OF FRAUD*[c]	33.0	17.5	49.5	5.56

Importance of fraud risk assessment when investing	Important (7,6,5)	Not unimportant or important (4)	Not important (3,2,1)	Response mean
18. *FRA*[d]	67.0	19.1	13.9	5.24

Use of red flags	Often (7,6,5)	Sometimes (4)	Rarely (3,2,1)	Response mean	H_0:Avg rating = **4.91**
Panel C					
19. *USE OF RED FLAGS*	65.5	26.3	8.2	**4.91**	
20. SEC investigation	72.6	18.6	8.8	5.28	***
21. Pending litigation	71.6	16.5	11.9	5.21	***
22. Violation of debt covenant	67.0	22.7	10.3	5.15	**
23. High management turnover	67.1	21.6	11.3	5.14	**
24. Insider trades	63.4	23.7	12.9	5.13	*
25. Abnormally high valuation ratios	66.5	21.6	11.9	5.08	
26. Large difference between net income and cash flow from operations	66.0	20.1	13.9	5.01	
27. Anticipated merger or acquisition	68.0	18.6	13.4	5.01	
28. Abnormally high revenue growth	63.9	24.2	11.9	5.00	
29. Large change in a reserve account	63.9	24.2	11.9	4.98	
30. Material weakness in internal control	61.4	23.7	14.9	4.93	
31. Equity-based compensation	61.9	24.2	13.9	4.90	
32. Recent stock or debt issuance	60.9	24.7	14.4	4.84	
33. Large difference in revenue growth and non-financial measures growth	59.8	23.7	16.5	4.82	

Table 1 continued

Use of red flags	Often (7,6,5)	Sometimes (4)	Rarely (3,2,1)	Response mean	H_0:Avg rating = **4.91**
34. Abnormal decline in non-financial measures	59.3	24.7	16.0	4.79	
35. Auditor change	57.8	24.2	18.0	4.74	
36. Number of insiders on board of directors	56.7	24.2	19.1	4.71	*
37. Age of firm	52.6	24.7	22.7	4.65	**
38. Need for external financing	55.1	29.4	15.5	4.64	**
39. Size of firm	55.1	25.8	19.1	4.60	***
40. Use of non-Big 4 auditor	49.7	25.3	24.7	4.42	***

[a] 194 respondents were asked to indicate the level of importance of information on a scale of 1 (not important) to 7 (very important). See footnote 11 for information about accessing the actual questions and response scales posed to survey participants. Columns 2–4 present the percent of respondents indicating "important" (7,6,5), "neutral" (4), and "not important" (3,2,1). The final column reports the results of a *t* test of the null hypothesis that the mean response for each "financial information" item and each "other information" item equals the mean response for all sources of financial information (Item 1) or other information (Item 8), respectively. ***, **, * denote rejection at the 1, 5, and 10 % levels, respectively

[b] Item 16, *RFI/ROI*, equals the ratio of mean reliance on financial statement information to mean reliance on other information (i.e., item 1/item 8). Columns 2–4 represent the percent of respondents whose *RFI/ROI* falls above, equals, or is below 1, respectively

[c] Item 17, *PERCEPTION OF FRAUD*, is the response to the question, "In your opinion, how often do managers of publicly traded companies commit financial statement fraud?" Responses were measured on a scale of 1 (0 % of the time) to 11 (100 % of the time). Columns 2–4 represent the percent of respondents indicating managers are likely to commit fraud in a majority (a response of 11–7), half (a response of 6), or a minority (a response of 5–1) of firms

[d] Item 18, *FRA*, is the response to the question, "How important is your assessment of the risk of financial statement fraud, relative to other factors, when making buy/sell decisions for stocks that you currently hold in your portfolio?" Responses were measured on a scale of 1 (not important) to 7 (very important). Columns 2–4 represent the percent of respondents indicating "important" (7,6,5), "neutral" (4), and "not important" (3,2,1), respectively

[e] 194 respondents were asked to indicate how often they used each factor in assessing the risk of financial statement fraud on a scale of 1 (never) to 7 (often). See footnote 11 for information about accessing the actual questions and response scales posed to survey participants. Columns 2–4 present the percent of respondents indicating "often" (7,6,5), "sometimes" (4), and "rarely" (3,2,1). *USE OF RED FLAGS* (item 19) is calculated as the mean response to items 20–40. The final column reports the results of a t-test of the null hypothesis that each average response equals the mean response for *USE OF RED FLAGS*. ***, **, * denote rejection at the 1, 5, and 10 % levels, respectively

Table 2 Descriptive statistics—control variables

Demographic data				Percentage
Panel A[a]				
1. Bought or sold individual company stock in the last 12 months		(Screening question)		100.00
2. Earned *UNDERGRADUATE DEGREE*				72.20
3. Earned *UNDERGRADUATE BUSINESS-RELATED DEGREE*				15.97
4. Earned *GRADUATE BUSINESS-RELATED DEGREE*				9.79
5. Earned a CPA, CFA, or CFP, *CERTIFIED*				17.01
6. *GENDER (% Male)*				51.03
7. *OWNED THE STOCK OF A FRAUD COMPANY*				24.74
Highest level of education	Graduate or Post Grad 5–4	Undergrad Degree 3	H.S. - Some College 2–1	Response mean
8. *EDUCATION*	39.7	32.5	27.8	3.22
Age	>60 (8,7,6)	40–59 (5,4)	<40 (3,2,1)	Response mean
9. *AGE*	19.8	51.3	28.9	4.31
Income	>$120 K (6,5)	$60–120 K (4,3)	<$60 K (2,1)	Response mean
10. *HOUSEHOLD INCOME*	16.5	46.4	37.1	3.18
Expected to recover loss from a fraud	Likely (7,6,5)	50–50 (4)	Unlikely (3,2,1)	Response mean
11. *LOSS RECOVERY*	25.8	24.2	50.0	3.37

Table 2 continued

Rely on advice from others or own analysis	Own analysis (7,6,5)	Equal (4)	Advice (3,2,1)	Response mean
12. *RELY ON OTHERS VS. OWN ANALYSIS*	36.6	35.6	27.8	4.05

Reliance on others to detect and report fraud	Likely to rely (7,6,5)	Equally likely as not to rely (4)	Unlikely to rely (3,2,1)	Response mean	H_0:average rating = **4.56**
Panel B[b]					
13. Mean *RELIANCE ON OTHERS*	49.5	40.2	10.3	**4.56**	
14. Regulators	63.4	26.3	10.3	5.02	***
15. External auditors	59.3	26.3	14.4	4.87	***
16. Analysts	60.4	27.2	12.4	4.80	**
17. Audit committee	46.9	34.5	18.6	4.56	
18. Investors	50.5	35.6	13.9	4.54	
19. Internal auditors	47.4	32.0	20.6	4.52	
20. Internal controls	46.9	36.6	16.5	4.52	
21. Upper management	43.8	32.0	24.2	4.35	**
22. Low/mid-level employees	45.4	30.9	23.7	4.33	**
23. Media	46.4	30.9	22.7	4.31	**
24. Short sellers	43.3	35.1	21.6	4.30	**

Investing experience, activity, and return	>15 years (7,6,5)	11–15 years (4)	<11 years (3,2,1)	Response mean
Panel C[c]				
25. *INVESTING EXPERIENCE*	22.6	15.5	61.9	3.35

Table 2 continued

	>6 h (7,6,5)	5–6 h (4)	<5 h (3,2,1)	Response mean
26. *TIME ALLOCATED (per week)*	12.4	11.3	76.3	2.64
	>15 times (5,4)	11–15 times (3)	<11 times (2,1)	Response mean
27. *TRADING ACTIVITY (per year)*	18.0	13.4	68.6	2.10
	>15 companies (5,4)	11–15 companies (3)	<11 companies (2,1)	Response mean
28. *DIVERSIFICATION OF INVESTMENTS*	5.7	18.0	76.3	1.82
	>$250 K (8,7,6)	$50 K–249 K (5,4)	<$50 K (3,2,1)	Response mean
29. *VALUE OF PORTFOLIO*	28.3	36.1	35.6	4.25
	>5 % (11,10,9,8)	−5–5 % (7,6,5)	<−5 % (4,3,2,1)	Response mean
30. *RETURN ON INVESTMENTS*	39.7	27.8	32.5	6.12
Investment strategies	Often (7,6,5)	Sometimes (4)	Rarely (3,2,1)	Response mean
Panel D[d]				
31. *GROWTH STOCK STRATEGY*	60.3	26.3	13.4	4.75
32. *FAMILIARITY WITH THE COMPANY*	54.6	26.8	18.6	4.70
33. *HIGH-YIELD STOCK STRATEGY*	53.1	30.4	16.5	4.52
34. *STRATEGY BASED ON TECHNICAL ANALYSIS*	48.4	32.5	19.1	4.45

Table 2 continued

Investment strategies	Often (7,6,5)	Sometimes (4)	Rarely (3,2,1)	Response mean
35. *LOW-RISK STOCK STRATEGY*	47.4	29.4	23.2	4.41
36. *VALUE STOCK STRATEGY*	42.8	40.2	17.0	4.38
37. *MOMENTUM STRATEGY*	30.4	39.7	29.9	3.90
38. *LAST YEAR'S WINNER STRATEGY*	28.4	33.5	38.1	3.70
Industries (% invested heavily in)				Percentage
39. *ENERGY*				41.23
40. *HIGH TECH/COMMUNICATIONS*				40.72
41. *MANUFACTURING*				32.98
42. *HEALTHCARE/PHARMACEUTICALS*				29.38
43. *FINANCIAL SERVICES*				25.77
44. *RETAIL*				22.16
45. *MISCELLANEOUS (OTHER)*				6.70

[a] 194 participants were asked to respond to the following statement (screening question): "I have bought or sold individual company stock in the last 12 months." Participants could respond "yes" or "no." See footnote 11 for information about accessing the actual questions and response scales posed to survey participants

[b] 194 respondents were asked to what extent they relied on each party (Items 14–24) to detect and report financial statement fraud on a scale of 1 (not at all) to 7 (completely). See footnote 11 for information about accessing the actual questions and response scales posed to survey participants. Columns 2–4 present the percent of respondents indicating they are "likely to rely" (7,6,5), "equally likely as not to rely" (4), and "unlikely to rely" (3,2,1). *RELIANCE ON OTHERS* is calculated as the mean response to items 14–24. The final column reports the results of a t-test of the null hypothesis that each average response is equal to the mean response for *RELIANCE ON OTHERS*. ***, **, * denote rejection at the 1, 5, and 10 % levels, respectively

[c] See footnote 11 for information about accessing the actual questions and response scales posed to survey participants

[d] 194 participants were asked "How often do you use the following investment strategies in your decisions to buy or sell stocks?" Responses were on a scale of 1 (never) to 7 (often). Results are summarized in items 31–38. Columns 2–4 present the percent of respondents indicating they "often" (7,6,5), "sometimes" (4), and "rarely" (3,2,1) use these sources. Participants were then asked, "In what industries do you most often buy and sell stocks of individual companies?" Responses were coded 1 if participant selected the industry, 0 otherwise. The percentage of participants who selected each industry is summarized in items 39–45

2008).[9] Additionally, our sample appears consistent with the samples of nonprofessional investors studied in Barber and Odean (2001) and Elliott et al. (2008). Barber and Odean (2001) examine 35,000 individual accounts held by a large discount brokerage firm. Investors studied in Barber and Odean (2001) held, on average, four individual stocks. In our study, participants report holding shares in 1–5 individual companies, on average. The average portfolio size of investors in Barber and Odean (2001) was \$47,000. Investors in our sample report an average portfolio value between \$50,000–\$99,000. Similar to our sample, the average income of investors in Barber and Odean (2001) was \$75,000.[10]

Finally, our sample appears consistent with that studied by Elliott et al. (2008). Although the average age reported by investors by Elliott et al. (2008) was slightly older (50–59 years) than the average age reported by investors in our study (40–49 years), investors in both studies reported similar levels of education (75 % of investors held at least an undergraduate degree), investing experience (Elliott et al.'s average investing experience was 9.92 years), and average number of trades per year (Elliott et al.'s average number of trades per year was 8.25). The similarities between our sample and those studied in prior research provide additional assurance about (1) the representativeness of our sample to the population of nonprofessional investors and (2) the accuracy of our investors' self-reported information. We provide a more detailed discussion of demographic data, as well as other control variables, in our review of descriptive statistics in Sect. 4.

3.2 Regression models

In H1a (*H1b*), we hypothesize that the importance investors place on conducting fraud risk assessments increases as their perception of the rate of fraud in the economy increases (*their reliance on financial statement information increases*). To test H1a and H1b, we estimate the following model via ordinal regression:

$$\begin{aligned} FRA_i = \beta_0 + \beta_1 PERCEPTION\ OF\ FRAUD_i + \beta_2 RFI/ROI_i \\ + \beta_{3-35} CONTROL\ VARIABLES_i + \varepsilon_i (\text{Model } 1) \end{aligned}$$

Our dependent measure is the investor's belief regarding the importance of fraud risk assessment when investing (FRA_i). Investors were provided with a definition of financial statement fraud and were asked, "How important is your assessment of the

[9] Data from the ICI indicate that 54 % of households with income between \$50,000 and \$74,999 and 69 % of households with income between \$75,000 and \$99,999 held individual securities. In addition, for individuals who held securities, 67 % had completed four years of college. Seventy-five percent of individuals who had completed some graduate school or obtained a graduate degree held individual securities (ICI 2008).

[10] We also compare the findings of Barber and Odean (2001) to certain participant-reported information gathered in our study regarding trading behavior and returns. Barber and Odean (2001) find that males trade more than females but realize lower returns. Results (not tabulated) from our survey participants are consistent. Males in our study report more trades per year than females ($p = 0.02$); however, the average return of these males is lower than that of the females ($p = 0.04$).

risk of financial statement fraud, relative to other factors, in making buy/sell decisions for stocks that you currently hold in your portfolio?"[11]

PERCEPTION OF FRAUD$_i$ is investor i's response to the question, "In your opinion, how often do managers of publicly traded companies commit financial statement fraud?" Participants responded on an 11-point scale, with 1 = "0 % of the time" and 11 = "100 % of the time." *RFI/ROI*$_i$ is a ratio defined as investor i's reliance on financial statement information relative to other forms of information (e.g., advice from professionals). Elliott et al. (2008) illustrate that nonprofessional investors use many information sources when investing. This ratio reflects this finding and is consistent with the measure used by Elliott et al. (2008). To obtain *RFI/ROI*$_i$, we divide the average of investor i's responses regarding the importance of particular financial statement information (e.g., balance sheet) to his investing decisions by the average of his responses regarding the importance of other sources of information when investing (e.g., advice from professionals).

The regression also includes several control variables that could influence *PERCEPTION OF FRAUD*$_i$, *RFI/ROI*$_i$, or *FRA*$_i$. We describe our control variables in Sect. 4. H1a (*H1b*) is supported if *PERCEPTION OF FRAUD*$_i$ (*RFI/ROI*$_i$) is positive and significant.

H2 predicts a positive association between the importance investors place on conducting a fraud risk assessment and their use of fraud red flags. To test H2, we estimate the following model via ordinary least squares regression:

$$USE\ OF\ RED\ FLAGS_i = \beta_0 + \beta_1 FRA_i + \beta_{2-34} CONTROL\ VARIABLES_i + \varepsilon_i (\text{Model 2})$$

Investor participants were asked how often they considered 21 different factors to assess the risk that a firm's financial statements were fraudulent. The variable, *USE OF RED FLAGS*$_i$, is the average of investor i's responses to this question posed for each of the 21 red flags. H2 is supported if *FRA*$_i$ is positive and significant.

4 Results

4.1 Descriptive statistics—hypothesized variables

Descriptive statistics for our hypothesized variables are presented in Table 1. In Panel A, we present mean responses and frequency distributions for our measures of financial statement reliance (items 2–7) and reliance on other information (items 9–15). Each is measured via a seven-point scale, with 1 = "very unimportant" and 7 = "very important." The mean for reliance on financial statement information (5.13, item 1) is significantly greater ($p < 0.01$) than the mean for reliance on other information (4.70, item 8).

[11] See the version of the paper available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1460820 for Appendices A and B, which contain the exact questions and response scales posed to investor participants to obtain our hypothesized and control variables.

With respect to financial statement information, investors rely more on balance sheet data and less on footnotes to the financial statements. In relation to other information sources, investors rely more on stock price, advice from professionals, and company risk. They rely less on nonfinancial information related to operations, advice from the media, and advice from nonprofessionals. See statistical tests in the far right column of Table 1, Panel A.

In Panel B, we calculate a relative measure of financial statement reliance (item 16) for each participant by dividing item 1 by item 8. This measurement, *RFI/ROI*, is an independent variable in Model 1. Panel B also provides descriptive statistics for the variables, *PERCEPTION OF FRAUD* (item 17) and *FRA* (item 18). The mean response for *PERCEPTION OF FRAUD* was 5.56, indicating that investors perceive fraudulent reporting to occur at 40–50 % of publicly traded companies.[12] This finding may be due, in part, to the fact that approximately 25 % of our sample reported owning shares of a company when it was found to have committed financial reporting fraud (see item 7 in Table 2, Panel A).[13] Such a high perception may also be fostered by media reports of the current rate at which financial statements are intentionally manipulated or managed (Guerrera 2012).

Given this finding regarding investors' perception of the rate of fraud, one would expect that conducting a fraud risk assessment, relative to other activities, would be an important component of investment decision making. Participants rated the importance of fraud risk assessment (*FRA*) using a seven-point scale, with 1 = "not at all important" and 7 = "very important." The mean response of 5.24 (item 18, Table 1) indicates that, on average, investors perceive fraud risk assessment to be a relatively important investment activity.

In Panel C of Table 1, we provide data on investors' use of 21 fraud red flags (items 20–40). Regarding their use of each red flag, participants responded to a seven-point scale, where 1 = "never" and 7 = "often." For each participant, we calculate his or her mean use of red flags. This variable, *USE OF RED FLAGS*, is the dependent variable in Model 2. The mean use of red flags for our sample is 4.91 (item 19).

With respect to the red flags investors indicate using most often, we find that investors focus on SEC investigations, pending litigation, violation of debt

[12] While the rate at which fraud is perpetrated is unknown, it is likely that our participants' perception of this rate is, on average, higher than the actual rate. Still, investors' perceptions are their reality and likely affect their subsequent actions (e.g., assessment of fraud risk, use of red flags). Our framework tests these relations.

[13] To be clear, we do not believe that either of these percentages (*PERCEPTION OF FRAUD* or *OWNED THE STOCK OF A FRAUD COMPANY)* represents an estimate of the actual rate of fraud across publicly traded companies. Rather, they likely represent that a substantial portion of investors have held the stock of at least one fraud firm. Given the size of the market capitalizations of companies that have committed fraud (e.g., Enron, WorldCom, HealthSouth, Waste Management, Xerox, etc.), investors who had a portfolio of any reasonable size likely held some shares of one of those companies. As expected, *OWNED THE STOCK OF A FRAUD COMPANY* and *PERCEPTION OF FRAUD* are positively correlated ($p <$ 0.01) for our sample.

covenants, and high management turnover (see items 20–23).[14] As discussed below, these red flags likely occur in the later stages of a fraud and are more easily acquired and interpreted by investors. Investors rely significantly less on the number of insiders on the board of directors, age of the company, need for external financing, company size, and use of a non-Big 4 auditor (see items 36–40). See statistical tests in the far right column of Table 1, Panel C.

Greater use of late-stage red flags (e.g., SEC investigation) may be related to increased difficulty in acquiring and evaluating early-stage red flags. Late-stage red flags are likely reported by the media, which increases their visibility. As such, they are likely more easily acquired than early-stage red flags that lack such visibility. Additionally, late-stage red flags are clearer indicators that something is amiss. That is, they are more easily evaluated as red flags. However, when a late-stage flag becomes present, the company stock price may already reflect concerns of fraud (Christensen et al. 2010).

With early-stage red flags, investors may be unsure at which level these measures suggest fraud. Additionally, early-stage red flags may be difficult to interpret in isolation. For example, high revenue growth may not appear abnormal unless it accompanies changes in nonfinancial measures that do not support growth (e.g., decrease in employees). However, nonfinancial measures are not reported on the income statement with revenue. In additional analyses, we investigate whether investors benefit from the use of early-stage red flags. If analyzing early-stage red flags helps to avoid fraudulent investments, regulators, investor protection groups (e.g., FINRA), and brokerages may need to consider ways to make these red flags more transparent (Schapiro 2011).

4.2 Descriptive statistics—control variables

Investors' decision making is likely influenced by a host of factors that may or may not be fraud related. To ensure the reliability of our results and to account for omitted correlated variables, we control for numerous variables that could affect investors' perceptions of the rate of fraud, their use of financial information, the importance they place on fraud risk assessment, and their use of red flags. (See footnote 11 for instructions on accessing the survey completed by investors.) We present descriptive statistics for these control variables in Table 2.

Consistent with Bertaut (1998), Masters (1989), Barber and Odean (2001), and Elliott et al. (2008), we control for a host of demographic data including education (items 2–4 and 8), professional licenses (item 5), age (item 9), and income (item 10). Intuitively, one would expect that prior fraud experiences (item 7), the perception that losses due to fraud can be recovered (item 11), and reliance on other parties to detect and report fraud (items 14–24) could impact our hypothesized variables.

[14] Investors may obtain certain red flags (e.g., debt covenant violations) from the popular press, investor websites, etc. (versus company disclosures). For two examples see: http://www.globalne.ws/Latest/D/4028810e3cf657a6013cf97b5f335e26/Poseidon-Concepts-admits-debt-covenant-violation,-has-entered-negotiations-with-its-lenders and http://www.streetinsider.com/Analyst+EPS+Change/Wells+Fargo+Downgrades+Penn+Virginia+Resource+Partners+(PVR)+to+Market+Perform/8119602.html.

While we use the mean *RELIANCE ON OTHERS* to detect and report fraud (item 13) as a control variable in our analyses, Panel B illustrates that investors see various capital market participants as more or less responsible in this area. For each party, reliance was measured on a seven-point scale ranging from 1 = “not at all” to 7 = “completely.” Results indicate that investors rely more on regulators, external auditors, and analysts to detect and report fraud (items 14–16). Investors rely less on upper management, low/mid-level employees, the media, and short sellers to uncover fraud (items 21–24). Interestingly, these perceptions run counter to recent evidence suggesting that the media, employees, analysts, and short sellers are all more likely than auditors and the SEC to detect fraud (Dyck et al. 2010). Overall, mean *RELIANCE ON OTHERS* to detect and report fraud was moderate (4.56, item 13).

Consistent with Elliott et al. (2008) and Barber and Odean (2001), we control for a number of other variables related to participants’ investing experiences, activities, and returns (items 25–30, Panel C).[15] These measures suggest that our sample consists of a diverse and experienced set of active investors. Item 25 illustrates that 22.6 percent of our sample has actively invested for over 15 years.

As suggested by prior research (e.g., Markowitz 1952; Elliott et al. 2008), we also control for participant trading strategies (items 31–38, Panel D). Given that fraud may be more prevalent in certain industries (e.g., Dechow et al. 2011), we control for the industries in which participants invest most heavily (items 39–45, Panel D). The results indicate that investors in our sample employ a diverse set of investment strategies and invest in a wide array of industries.

Finally, we use these descriptive measures to identify investor characteristics that are related to *PERCEPTION OF FRAUD* and *RFI/ROI*. Providing a composite sketch of investors who deem the rate of fraud in the economy to be higher or who rely more on financial statement information contributes to our understanding in this area and may spur future research. In non-tabulated analyses, we examine the relations between our control variables in Table 2 and *PERCEPTION OF FRAUD* and *RFI/ROI*. These analyses reveal that investors who perceive the rate of fraud in the economy to be higher tend to have been a victim of a past fraud, rely less on others to detect fraud (which is likely why they perceive the rate to be higher), are more likely to rely on their own analyses (particularly technical analysis), are apt to believe they can recover losses through shareholder lawsuits, are less likely to

[15] Participants in our study took the survey from August 21 to 25, 2008. We asked them to approximate their return on their investment portfolio for the last 12 months on a scale of 1 (less than −20 %) to 11 (more than 20 %). The average response was 6.12 (approximately a 0 % return). While the average return for the NYSE was negative during that time frame, Table 2, Panel D, shows that the most popular industries of investment for our participants were energy/utilities, high tech/communications, and manufacturing. The energy/utilities industry survived the 2008 recession less scathed than others. Several firms in the industry even reported positive returns during the period we examined (e.g., Duke Energy, NextEra Energy, New Jersey Resources, NorthEast Utilities, and Pacific Gas and Electric). Biotech companies and manufacturers of consumer staples also fared well during this time period (e.g., Biogen, Bristol Myers Squibb, Colgate Palmolive, Diamond Foods, General Mills, Heinz, Hormel Foods, Hershey Foods, and Kellogg). See http://seekingalpha.com/article/620081-stocks-that-declined-least-in-2008-crash-and-2010-and-2011-corrections. Therefore, given the industries invested in by our survey participants and the lack of diversification of their portfolios (see Table 2, Panel C), the average reported return being above the average return for the NYSE is not surprising.

Table 3 Correlation matrix

Variables[a]	*RFI/ROI*	*PERCEPTION OF FRAUD*	*FRA*	*USE OF RED FLAGS*
PERCEPTION OF FRAUD	**−0.18**			
FRA	−0.01	**0.21**		
USE OF RED FLAGS	−0.09	**0.29**	**0.51**	
LOSS RECOVERY	**−0.21**	**0.40**	0.05	0.12
RELIANCE ON OTHERS	**−0.24**	**0.21**	**0.34**	**0.58**
TIME ALLOCATED	0.04	**0.17**	**0.23**	**0.32**
RETURN ON INVESTMENTS	−0.06	0.05	**0.26**	**0.24**
DIVERSIFICATION OF INVESTMENTS	0.01	**0.17**	0.06	**0.14**
MOMENTUM STRATEGY	**−0.17**	**0.25**	**0.22**	**0.30**
GROWTH STOCK STRATEGY	−0.01	0.12	**0.29**	**0.45**
LOW-RISK STOCK STRATEGY	−0.12	**0.21**	**0.30**	**0.42**
LAST YEAR'S WINNER STRATEGY	**−0.25**	**0.32**	**0.27**	**0.40**
VALUE STOCK STRATEGY	**−0.15**	**0.26**	**0.30**	**0.51**
HIGH-YIELD STOCK STRATEGY	**−0.16**	**0.19**	**0.41**	**0.49**
STRATEGY BASED ON TECHNICAL ANALYSIS	**−0.21**	**0.29**	**0.29**	**0.42**
FAMILIARITY WITH THE COMPANY	**−0.18**	**0.17**	**0.22**	**0.40**
MISCELLANEOUS INDUSTRIES	0.01	**−0.20**	**−0.21**	**−0.21**
GENDER	0.05	**−0.15**	**−0.19**	−0.09

Pearson correlation statistic. Correlations with p values <0.05 are in boldface type

[a] See footnote 11 for information about accessing the actual questions and response scales posed to survey participants

invest in the high tech/communication companies, and have smaller investment portfolios.

Investors who tend to rely directly on financial statements when investing report spending more time analyzing companies (likely due to their direct review of financial statements), appear to follow growth stocks and not use a "last year's winners" investing strategy, are less likely to invest in the retail and healthcare/pharmaceuticals industries (suggesting that financial statements in these industries are less useful to investors), and, surprisingly, are less likely to be certified as a CPA, CFA, etc. (However, we will observe below that various measures of financial expertise are also not associated with the use of red flags.)

4.3 Correlation matrix

A correlation matrix is presented in Table 3. To be parsimonious, control variables were excluded from presentation if they were not significantly correlated ($p < 0.05$) with at least two of the four hypothesized variables (e.g., *PERCEPTION OF FRAUD*, *RFI/ROI*). Reducing this constraint from two to one led to a substantially larger correlation matrix. We do not tabulate correlations between control variables.

Of particular note, and consistent with our development of H1a, *PERCEPTION OF FRAUD* is significantly and positively correlated with *FRA*. However, *RFI/ROI* is not significantly correlated with *FRA*. While this finding does not provide initial support for H1b, we hypothesize that *RFI/ROI* is significantly correlated with *FRA* after controlling for potentially confounding variables (e.g., *RELIANCE ON OTHERS*, *LOSS RECOVERY*). Therefore we re-examine this association in our multivariate analysis below.[16] While we do not hypothesize a relation between *PERCEPTION OF FRAUD* and *RFI/ROI*, we observe a significant negative relation. This suggests that investors turn to other sources of information (e.g., advice from professionals) when they perceive the risk of financial reporting fraud in the economy to be higher. Consistent with H2, *FRA* is significantly positively correlated with the *USE OF RED FLAGS*. We formally test H1a, H1b, and H2 in multivariate settings below.

4.4 Hypotheses testing

H1a (*H1b*) predicts that the importance investors place on conducting fraud risk assessments increases as their perception of the rate of fraud in the economy (*their reliance on financial statement information*) increases. Table 4 presents the results of H1a and H1b testing. For presentation purposes, only effects related to control variables with p values <0.10 are tabulated. Importantly, the main effects for both *PERCEPTION OF FRAUD* and *RFI/ROI* are significant (p's < 0.05). Thus, controlling for potentially confounding variables, our multivariate regression results provide support for both H1a and H1b. Investors place more importance on conducting a fraud risk assessment when perceiving a relatively higher frequency of fraud in the economy or when they tend to rely on financial statements relative to other information.

H2 predicts a positive association between the importance of fraud risk assessment and use of red flags. Table 5 presents the results of our H2 testing. We find the relation between *FRA* and *USE OF RED FLAGS* is positive and significant ($p < 0.01$), supporting H2. Investors who believe in the importance of conducting a fraud risk assessment act on that belief by using red flags to avoid investing in potentially fraudulent companies.[17]

[16] See Doyle et al. (2007) for a similar examination with respect to the association between firm size and internal control weaknesses. They note firm complexity could be a confounding variable. As such, they do not observe a significant, bivariate correlation between size and internal control weaknesses but find a significant relation between these two variables when they control for confounding variables, such as firm complexity.

[17] While *USE OF RED FLAGS* is the average of survey participants' reported use of all individual red flags, in Sect. 2.1 we describe how individual red flags can be categorized based on the fraud triangle (i.e., incentive, opportunity, or attitude) as well as comparisons between financial and nonfinancial information. As such, we assigned red flags to these categories and re-performed our test of H2. In untabulated analyses, we observe that the relation between *FRA* and each category is positive and highly significant (p's < 0.01). Thus it does not appear that investors who perceive fraud risk as important favor the use of red flags in any one of these categories.

Table 4 H1a and H1b testing: ordinal regression for *FRA*

Independent variables	Predicted sign	Estimated coefficient	Wald-statistic	*p* value
PERCEPTION OF FRAUD[a]	+	0.145	4.13	0.021
RFI/ROI[b]	+	1.090	3.86	0.025
CONTROLS[c]				
LOSS RECOVERY	−	−0.255	6.12	0.013
RELIANCE ON OTHERS	−	0.335	3.58	0.058
RETURN ON INVESTMENTS	+	0.125	4.61	0.032
LAST YEAR'S WINNER	?	0.240	3.09	0.079
HIGH YIELD	?	0.258	3.18	0.074
GENDER	?	−0.630	4.22	0.040
FINANCIAL SERVICES	?	0.809	4.61	0.032
HOUSEHOLD INCOME	?	−0.253	3.66	0.056
Model Chi Square statistic = 84.06 (p value <0.001)				
$R^2 = 0.352$				

See footnote 11 for information about accessing the actual questions and response scales posed to survey participants

FRA = importance of fraud risk assessment, relative to other factors, when making buy/sell decisions for stock that you currently hold. Measured on a scale where 1 = "not at all important" and 7 = "extremely important"

[a] *PERCEPTION OF FRAUD* = in your opinion, how often do managers of publicly traded companies commit financial statement fraud? Measured on a scale where 1 = "0 %" and 11 = "100 %"

[b] *RFI/ROI* = ratio of mean reliance on financial statement information (*RFI*) to mean reliance on other information (*ROI*)

[c] Only effects related to control variables with *p* values <0.10 are tabulated

4.5 Mediation analysis of the framework

Given the support we find for H1a, H1b, and H2, we examine whether the importance of fraud risk assessment (*FRA*) mediates the effects of *PERCEPTION OF FRAUD* and *RFI/ROI* on the *USE OF RED FLAGS*. Following Zhao et al. (2010), we conduct a mediation analysis to determine the validity of the framework presented in Fig. 1.

We first conduct the Preacher–Hayes (2008) bootstrap test of mediation. To do so, we model the following three equations:[18]

$$\begin{aligned} FRA_i = i_0 + a PERCEPTION\ OF\ FRAUD_i\ (or\ a RFI/ROI_i) \\ + \beta_{1-8} CONTROL\ VARIABLES_i + \varepsilon_i \end{aligned} \tag{1}$$

[18] The three equations include all control variables that were significant in Table 4. For ease of interpretation, the coefficient variable terms (e.g., *a*, *b*, *c*, *c'*) and other terminology are the same as those used by Zhao et al. (2010). Prior research had relied on the Sobel (1982) test (e.g., Baron and Kenny 1986) to test mediation; however, Zhao et al. (2010, p. 22) explain why the Preacher-Hayes bootstrap test is superior to the Sobel (1982) test. A macro to run the Preacher-Hayes test in SAS and SPSS can be found at http://www.afhayes.com/spss-sas-and-mplus-macros-and-code.html.

Table 5 H2 testing: linear regression for *USE OF RED FLAGS*

Independent variables	Predicted sign	Estimated coefficient	*t*-statistic	*p* value
FRA[a]	+	0.198	4.28	<0.001
CONTROLS[b]				
RELIANCE ON OTHERS	−	0.364	4.64	<0.001
VALUE OF PORTFOLIO	+	−0.097	2.20	0.029
MANUFACTURING	?	0.298	2.14	0.034
ENERGY	?	0.387	2.67	0.008
VALUE STOCK STRATEGY	?	0.148	2.37	0.019
HOUSEHOLD INCOME	?	0.105	1.75	0.081
Model *F*-statistic = 7.73 (*p* value <0.001)				
$R^2 = 0.623$				

See footnote 11 for information about accessing the actual questions and response scales posed to survey participants

USE OF RED FLAGS = mean use of red flags (mean of items 20–40 in Table 1)

[a] *FRA* = importance of fraud risk assessment, relative to other factors, when making buy/sell decisions for stock that you currently hold, measured on a scale where 1 = "not at all important" and 7 = "extremely important"

[b] Only effects related to control variables with *p* values <0.10 are tabulated

$$USE\,OF\,RED\,FLAGS_i = i_0 + c'PERCEPTION\,OF\,FRAUD_i\,(or\,c'RFI/ROI_i) + \beta_{1-8}CONTROL\,VARIABLES_i + \varepsilon_i \tag{2}$$

$$USE\,OF\,RED\,FLAGS_i = i_0 + cPERCEPTION\,OF\,FRAUD_i\,(or\,cRFI/ROI_i) + bFRA_i + \beta_{1-8}CONTROL\,VARIABLES_i + \varepsilon_i \tag{3}$$

The indirect effect of *PERCEPTION OF FRAUD* or *RFI/ROI* on *USE OF RED FLAGS* through *FRA* can be quantified as the product of *a* and *b*. According to Zhao et al. (2010), testing the significance of the indirect path is the one and only test required to establish mediation. The Preacher–Hayes (2008) test estimates the direction and significance of the indirect path ($a \times b$). The test is performed by generating an empirical sampling distribution of ($a \times b$). In our case, it draws with replacement 194 (i.e., N) values of *PERCEPTION OF FRAUD* (or *RFI/ROI*), *FRA*, and *USE OF RED FLAGS* to create a new sample. We generate 5,000 bootstrap samples and estimate Eqs. (1) and (3) for each, which generates 5,000 estimates of *a*, *b*, and ($a \times b$). The indirect effect is the mean of the estimates. The test generates a 95 % confidence interval. If the confidence interval does not contain zero, then we are 95 % confident that the indirect effect is different than zero (i.e., $p < 0.05$).

If the indirect path ($a \times b$) is significant, then we have evidence of mediation. If the indirect path ($a \times b$) is not significant, then there is no evidence of mediation. If the direct path (*c*) is also significant, then we have the possibility of complementary (i.e., indirect and direct paths have the same sign) or competitive mediation (i.e., indirect and direct paths have a different sign). If the direct path (*c*) is not significant, then we have only indirect mediation.

Table 6 Mediation analyses with *USE OF RED FLAGS* as the outcome measure and *FRA* as the mediator

Variable	Path	Estimated coefficient	SE	t-statistic	p value
PERCEPTION OF FRAUD[a]	a	0.090	0.044	2.05	0.042
	b	0.206	0.048	4.30	<0.001
	Total (c')	0.099	0.030	3.30	0.001
	Direct (c)	0.080	0.029	2.77	0.006
	Point estimate	SE	Confidence interval*		
			Lower	Upper	
($a \times b$)	0.019	0.010	0.002	0.044	
Variable	Path	Estimated coefficient	SE	t-statistic	p value
RFI/ROI[b]	a	0.572	0.363	1.57	0.117
	b	0.221	0.048	4.55	<0.001
	Total (c')	0.324	0.252	1.29	0.200
	Direct (c)	0.197	0.241	0.82	0.414
	Point estimate	SE	Confidence interval*		
			Lower	Upper	
($a \times b$)	0.126	0.099	−0.033	0.369	

Number of bootstrap re-samples = 5000. The indirect effect is statistically significant at the chosen level when the confidence interval does not include zero (95 % equals $p < 0.05$ level significance). See Sect. 4.5 for information about the models and paths tested

USE OF RED FLAGS = mean use of red flags (mean of items 20–40 in Table 1)

FRA = importance of fraud risk assessment, relative to other factors, when making buy/sell decisions for stock that you currently hold. Measured on a scale where 1 = "not at all important" and 7 = "extremely important"

PERCEPTION OF FRAUD = in your opinion, how often do managers of publicly traded companies commit financial statement fraud? Measured on a scale where 1 = "0 %" and 11 = "100 %"

See footnote 11 for information about accessing the actual questions and response scales posed to survey participants

* Confidence intervals are biased corrected for both median bias and skew

[a] *RFI/ROI* = ratio of mean reliance on financial statement information (*RFI*) to mean reliance on other information (*ROI*)

Table 6 presents the results of our mediation analyses. With respect to *FRA* mediating the effect of *PERCEPTION OF FRAUD* on *USE OF RED FLAGS*, we find a positive and significant ($p < 0.05$) indirect path ($a \times b$). In other words, the 95 % confidence interval does not include zero (Lower = 0.002, Upper = 0.044). In addition, we find a positive and significant ($p = 0.006$) direct path (c). Therefore we have complementary mediation. Specifically, investors who perceive the rate of fraud in the economy to be higher are using fraud red flags. This use is driven by the importance they place on conducting their own fraud risk assessments as part of their investment decision making.

With respect to *FRA* mediating the effect of *RFI/ROI* on *USE OF RED FLAGS*, we do not find a significant indirect path ($a \times b$). In other words, the 95 % confidence interval includes zero. Additionally, we do not find a significant ($p = 0.414$) direct path (c). Therefore we have no mediation. This finding and the results of H1b suggest that investors who primarily rely on financial statement information may deem fraud risk assessment to be important, but they are *not* including in their financial statement analyses red flags that could help to identify fraud. If this is the case, our evidence supports the SEC's call to make changes to increase the transparency of information that could signal fraud (Schapiro 2011).

4.6 Discussion of control variables in H1 and H2 testing

With respect to the effects of control variables on our dependent measures, as seen in Tables 4 and 5, several observed relations deserve attention. First, we find that investors in the financial services industry are more likely than other investors to place importance on conducting a fraud risk assessment (Table 4). The recent crisis in financial services may have increased investors' concern regarding fraud risk in this industry. We also note that investors in the manufacturing and energy industries are more likely than other investors to use red flags (Table 5). Whether red flags are more transparent or easier to analyze in these industries' reports, relative to those of other industries, is a fruitful area for future research. The energy industry relation may also stem from the Enron fraud.

Next, note the positive and significant relation between investor returns and fraud risk assessment (Table 4). In analyses that follow, we provide evidence of links between investor returns and the use of *specific* red flags. There is also a significant relation between gender and fraud risk assessment (Table 4), which indicates that males perceive fraud risk assessment to be less important than do females. This result comports with research in economics and finance indicating women to be more risk averse than men (e.g., Borghans et al. 2009).

While one would likely predict a positive association between the value of investors' portfolios and their use of red flags (Table 5), we observe a negative relation. Additional untabulated analyses indicate that the control variables, *VALUE OF PORTFOLIO* and *DIVERSIFICATION OF INVESTMENT*, are positively correlated ($p < 0.01$). That is, investors who have larger portfolios tend to be more diversified. These investors may be less affected by a fraudulent investment than investors holding smaller but less diversified portfolios. In turn, investors holding larger portfolios may be less likely to consider fraud red flags.

Interestingly, we find that the extent to which investors rely on others to detect and report fraud is positively related to the importance placed on their own fraud risk assessment and their personal use of red flags (Tables 4 and 5). Perhaps investors who are more likely to assess fraud risk and use red flags understand that multiple parties are responsible for fraud detection (Dyck et al. 2010). The shared responsibility to detect fraud and the synergies that may be realized from multiple stakeholders' assessments of fraud risk are fruitful areas for future research. Last, we do not find a significant association between *TRADING ACTIVITY* and either *FRA* or *USE OF RED FLAGS*. This suggests that investors who conduct fraud risk assessments through the use of red flags are confident in their abilities to determine the risk of fraud. That is, their assessments of fraud risk and use of red flags do not deter trading.

4.7 Supplemental analyses

4.7.1 Use of accruals as a red flag and investor portfolio returns

Lee et al. (1999) observe that high accrual levels are an indicator of fraud. Sloan (1996), however, finds that investors fixate on earnings and have difficulty distinguishing between earnings derived from cash flows and those derived from accruals.[19] As such, he finds a negative association between accruals and future abnormal stock returns. Ali et al. (2000) find, however, that the negative association between accruals and future stock returns is significantly stronger for larger firms, which are more likely to be followed by analysts and held by institutional investors (vs. smaller firms that are more likely held by nonprofessional investors). This counterintuitive result suggests that any failure to appreciate the valuation implications of accruals may be more pronounced for sophisticated investors than for less sophisticated investors.

Given our sample of experienced, nonprofessional investors, we are in a unique position to add to this research stream. Specifically, we have a measure of investors' usage of accrual data (item 26, Table 1) and investors' 12-month return on their personal investment portfolios (item 30, Table 2). In an untabulated regression controlling for the variables used by Elliott et al. (2008) in their analyses of investor returns, we find the relation between the consideration of the accrual red flag by nonprofessional investors and their portfolio returns to be positive and significant ($p = 0.04$).[20] As illustrated in Table 4, we also observe a positive and significant association between *FRA* and investor returns. Thus we can provide initial empirical evidence that nonprofessional investors may be achieving higher portfolio returns by assessing fraud risk and, in particular, using accrual data as part of their analyses.

[19] Complex analytical skills developed at higher levels of education may be necessary to collect and analyze red flags (e.g., accrual levels). Thus some forms of investor financial expertise, education, experience, or a combination of these may be associated with the use of the most effective red flags (e.g., the accrual red flag examined in this section and early-stage fraud red flags studied in Sect. 4.7.2). Interestingly, controlling for the variables provided in Table 2, we do not observe positive relations between either *INVESTING EXPERIENCE*, *EDUCATION*, or other measures of financial expertise and use of these particular red flags. In particular, the lack of a relation between our measures of financial expertise and the use of the most effective red flags is concerning and may reflect a lack of coverage of financial statement red flags in many business-related educational programs.

[20] We control for the variables used in Elliot et al. (2008) because they specifically examine the returns of nonprofessional investors. However, we do not include the variable "training" from Elliott et al. (2008), as it was specific to training provided by the investment club from which their sample was derived. Additionally, it was not statistically significant in their analysis.

Table 7 Linear regression for *USE OF EARLY-* and *LATE-STAGE RED FLAGS*

Independent variables	Predicted sign	Estimated coefficient	*t*-statistic	*p* value
Panel A—Dependent variable—*USE OF EARLY-STAGE RED FLAGS*[a]				
FRA[c]	+	0.219	4.44	<0.001
CONTROLS[d]				
RELIANCE ON OTHERS	–	0.382	4.56	<0.001
VALUE OF PORTFOLIO	+	−0.091	1.93	0.055
MANUFACTURING	?	0.338	2.28	0.024
ENERGY	?	0.450	2.91	0.004
VALUE STOCK STRATEGY	?	0.163	2.46	0.015
HOUSEHOLD INCOME	?	0.111	1.75	0.082
Model F-statistic = 7.16 (p value <0.001)				
$R^2 = 0.605$				
Panel B—Dependent variable—*USE OF LATE-STAGE RED FLAGS*[b]				
FRA[c]	+	0.181	3.32	0.001
CONTROLS[d]				
RELIANCE ON OTHERS	–	0.392	4.23	<0.001
VALUE OF PORTFOLIO	+	−0.121	2.34	0.021
MANUFACTURING	?	0.332	2.02	0.045
ENERGY	?	0.392	2.30	0.023
VALUE STOCK STRATEGY	?	0.144	1.96	0.051
GROWTH STOCK STRATEGY	?	0.137	1.81	0.073
LOW-RISK STOCK STRATEGY	?	0.101	1.72	0.087
Model F-statistic = 6.47 (p value <0.001)				
$R^2 = 0.581$				

See footnote 11 for information about accessing the actual questions and response scales posed to survey participants

[a] *USE OF EARLY-STAGE RED FLAG* = mean use of early-stage red flags (mean of items 23–35 in Table 1)

[b] *USE OF LATE-STAGE RED FLAG* = mean use of late-stage red flags (mean of items 20–22 in Table 1)

[c] *FRA* = importance of fraud risk assessment, relative to other factors, when making buy/sell decisions for stock that you currently hold, measured on a scale where 1 = "not at all important" and 7 = "extremely important"

[d] Only effects related to control variables with p values <0.10 are tabulated

4.7.2 Use of early-stage fraud red flags and investor portfolio returns

Panel C of Table 1 illustrates that the red flags investors report using most often are those that typically manifest in later stages of fraud.[21] Consequently, it is

[21] In Table 1, investors report using five fraud red flags relatively more often than other red flags: SEC investigations, pending litigation, violations of debt covenants, high management turnover, and insider trading. Although high management turnover and insider trading may occur at any point, the other three red flags can be considered late-stage fraud indicators.

questionable whether investors' attention and reaction to such *late-stage* red flags would (a) reduce the likelihood that they experience losses due to fraud and (b) increase their portfolio returns (Christensen et al. 2010). Indeed, in Table 5, we do not observe a significant relation between the *USE OF RED FLAGS* (our aggregate measure) and *RETURN ON INVESTMENTS*. Therefore we explore whether investors' use of *early-stage* fraud red flags leads to higher returns. We develop a measure of the use of early-stage fraud red flags for each participant (averaging their responses to items 23–35 from Table 1, Panel C) and include this measure in the model used by Elliott et al. (2008) to examine portfolio returns. In untabulated analyses, we find a positive and significant relation between the use of early-stage fraud red flags by nonprofessional investors and their portfolio returns ($p < 0.01$). This finding offers researchers, investors, and regulators with a shortened list of effective early-stage fraud red flags that investors are prone to use.

Although investors, in general, report greater use of late-stage red flags as opposed to early-stage red flags (Table 1, Panel C), we examine whether individuals who consider fraud risk assessment to be important (*FRA*) consider both early- and late-stage red flags. We re-estimate Model 2, replacing the dependent variable, *USE OF RED FLAGS*, with *USE OF EARLY-STAGE RED FLAGS* in one model and *USE OF LATE-STAGE RED FLAGS* in another model. Table 7 provides these results.

In Panel A, where *USE OF EARLY-STAGE RED FLAGS* is the dependent variable, the coefficient on *FRA* (0.219) is positive and significant ($p < 0.001$). In Panel B, where *USE OF LATE-STAGE RED FLAGS* is the dependent variable, the coefficient on *FRA* (0.181) is positive and significant ($p = 0.001$). Thus, while investors, in general, rely less on early-stage red flags, investors who consider fraud risk assessment to be more important rely on both early- and late-stage red flags.

5 Conclusion and future research

We find that when investors perceive fraudulent reporting to be more prevalent in the economy or rely more on financial statement information relative to other sources of information, they place greater importance on conducting their own fraud risk assessments. In turn, investors who deem fraud risk assessment to matter in investment decision making make greater use of fraud red flags to avoid potentially fraudulent investments.

In addition to these primary findings, our survey allows us to study many investor attributes, which serve in developing a profile of investors who are either more or less likely to include fraud risk assessment as part of their investment decisions. Regulators, who aim to protect individual investors (e.g., FINRA), can begin to educate the former on more advanced analyses of red flags (e.g., tools to help identify early-stage red flags and related benchmark data). For the latter group, regulators can use basic efforts to educate them on fraud risk and steps that can be taken to minimize losses due to fraud (e.g., a clean audit opinion does not constitute a forensic audit).

Results of the survey also indicate that investors, in general, are likely to use more obvious late-stage red flags than more beneficial early-stage red flags. This evidence supports calls to make disclosures of early-stage red flags more transparent (Schapiro 2011).[22] Regulator or investor websites could accumulate and disclose red flag data to assist investors in identifying companies that are beginning to exhibit multiple early-stage red flags. Additionally, we have evidence of the various parties upon whom investors rely to detect fraud. Interestingly, investors' perceptions of the parties who are responsible for fraud detection (e.g., auditors, regulators) run counter to recent evidence indicating the parties who have the greatest likelihood of catching fraud (e.g., short sellers, employees) (Dyck et al. 2010). Investors may lack awareness of both the responsibilities and incentives of various parties to detect and report fraud (e.g., McEnroe and Martens 2001). Education on and introduction to these parties could provide investors with other resources to consult in their decision making. In the end, our framework and descriptive results should inform future policies aimed at protecting investors from fraud, as standard setters have become increasingly concerned with the behavioral aspects of market participants and their use of red flags (e.g., Zweig 2009; Schapiro 2011).

At some point, investors' perceptions of the prevalence of fraud could be so heightened that they would be driven from investing in individual company stocks altogether. As we required investors in our study to have bought or sold company stock in the past 12 months, participants in the study had not met this boundary condition. We also acknowledge that the use of the survey method permits only measures of associations. However, we believe our results will lead to further research, employing multiple methods, in the area of investor fraud protection. In particular, we suggest the following questions for future research to examine. In an experimental setting where the presence of red flags is manipulated, what types of investors are more apt to detect and react to red flags? Are fraud red flags more transparent or easier to analyze in the financial reports of firms in certain industries? Fraud firms typically exhibit multiple red flags (e.g., Dechow et al. 2011; Hogan et al. 2008), and our data suggest that investors consider a variety of red flags. What is the tipping point, with respect to the number of red flags present, where an investor avoids investing in (or sells) a stock based on concerns over fraud? Can empirically-validated red flags be made more transparent and intuitive for nonprofessional investors? Continuation of such research will help standard setters make informed public-policy decisions designed to protect individual investors from financial reporting fraud.

Acknowledgments This study has benefited from comments provided by Chris Agoglia, Jagadison Aier, Ben Ayers, Linda Bamber, Michael Bamber, Mark Beasley, Paul Beswick, Frank Buckless, Tina Carpenter, Brian Croteau, Brooke Elliott, Blake Hetrick, Frank Hodge, Susan Krische, James Kroeker, Kathleen Linn, Molly Mercer, Jason Smith, Steve Smith, Hun-Tong Tan and input received from presentations to the Office of the Chief Accountant of the Securities and Exchange Commission, the Financial Industry Regulatory Authority (FINRA), the 2011 Conference of the Research Center on the

[22] For example, to aid investors in evaluating the validity of financial information, disclosures in firms' 10-Ks could present a more concise and centralized picture of changes in nonfinancial measures. See pages 39 and 40 of the Tenet Healthcare 2013 10-K for an example of such a transparent disclosure: http://api40.10kwizard.com/cgi/convert/pdf/THC-20140224-10K-20131231.pdf?ipage=9416838&xml=1&quest=1&rid=23&section=1&sequence=-1&pdf=1&dn=1.

Prevention of Financial Fraud, the 2012 Mid-Atlantic Region Conference for the Institute of Internal Auditors, and the 2012 Meeting of the Association of Certified Fraud Examiners—Central Carolina Chapter. This research was supported by a grant from the FINRA Investor Education Foundation. All results, interpretations, and conclusions expressed are those of the authors alone and do not necessarily represent the views of the FINRA Investor Education Foundation or any of its affiliated companies.

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