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Corporate fraud and the value of reputations in the product market

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ABSTRACT

We examine the consequences of a damaged reputation for fraud firms in the context of product markets. We generate three direct measures of reputational damage and find evidence that customers impose significant reputational sanctions on fraud firms. Using yearly transactional data to track the business dealings of fraud firms with large customers, we show that customer reputational sanctions result in a decline in the firm's operating performance through increased selling costs, as suggested by previous studies of corporate reputation. We further find that reputational losses estimated from an event study approach reflect the actual decrease in the revenue of a fraud firm, which suggests that the event study approach yields a reliable measure of reputational losses. Finally, we document that these findings are the result of a damaged reputation following the detection of fraud rather than an effect of adverse information revealed upon fraud detection.

1. Introduction

The consequences of a damaged reputation that results from corporate misconduct have been investigated extensively in previous studies (Alexander, 1999; Gande and Lewis, 2009; Karpoff and Lott, 1993; Karpoff et al., 2008a, 2008b). The existence of reputational losses associated with financial stakeholders, such as lenders and investors, is also well documented in the literature (Graham et al., 2008; Murphy et al., 2009). However, there is limited evidence of the imposition of significant reputational losses from financial misconduct by outside stakeholders of the firm apart from lenders and investors.[1]

Several theoretical studies predict that a damaged reputation has real consequences for fraud firms in the context of the product market. For instance, financial misconduct should have a large effect on the firm's contracting with customers (Klein and Leffler, 1981). Customers may be apprehensive in dealing with a firm that has dishonest management, thus, reducing their demand for the fraud firm's products. Hereafter, we refer to this unfavorable change in customer behavior as a customer reputational sanction.[2] This argument leads to the following questions that we will subsequently examine in this paper: Does financial misconduct cause the firm's customers to re-evaluate their business relationships with the firm, leading the fraud firm to

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[1] Where financial misconduct implies a vague notion of wrongdoing related to a firm's financial activities, fraud implies that the firm has made an explicit attempt to mislead for financial gains. While we recognize that there is a difference between financial misconduct and fraud, we use the terms interchangeably in our writing.

[2] There is anecdotal evidence supporting this argument. For instance, after it was accused of fraud, Splash Technologies disclosed that its "Sales, general, and administrative expenses are … expected to increase in future periods as the Company increases its sales support…to expand its presence in sales channels other than Xerox and Fuji…," both of which were its large customers at the time of the fraud. See Splash Technologies quarterly report, August 14, 2000. http://www.sec.gov/Archives/edgar/data/1020394/000091205700037178/0000912057-00-037178.txt.

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lose sales and bear the costs of building new customer relationships? Are these costs significant enough to become economically meaningful for fraud firms?

Previous studies provide incomplete answers to these questions. Most evidence about reputational losses comes from the event study approach that is implicit in Peltzman (1981) and Jarrell and Peltzman (1985), and explicit in Karpoff and Lott (1993). These studies estimate reputational losses as the change in firm value when a fraud is first revealed minus the legal penalties from the fraud.[3] However, there is limited direct evidence on whether the reputational losses imposed by customers and estimated from the event study approach reflect actual increases in the firm's costs or decreases in its revenues.

The investigation of possible reputational sanctions imposed by customers is empirically challenging because these sanctions coincide with the normal business exchange between a firm and its customers. Thus, when customers of fraud firms impose less favorable terms of trade on their fraud firm suppliers (Karpoff, 2010), these changes are typically hard to detect from the outside. Ideally, researchers need access to detailed transaction-level data about a series of business exchanges between the fraud firm and its customer around the time of fraud detection.

To overcome this empirical hurdle, we take a novel approach, which allows us to quantitatively measure the intensity of customer reputational sanctions based on the extensive data on the customer–supplier bilateral trading history. For this purpose, we utilize the COMPUSTAT segment level database, which contains comprehensive information about trading between a firm and its large customers. FAS No. 131 disclosure rules require firms to reveal all the customers that are responsible for over 10% of their annual revenues. The COMPUSTAT segment level database contains detailed supplier–customer data gleaned from these disclosures filed with the Securities and Exchange Commission (SEC), including information on customers that account for more than 10% of sales, along with data on the actual sales to the large customers.[4] This database is extensively used in previous studies, including Fee and Thomas (2004), Fee et al. (2006), and Hertzel et al. (2008).[5]

Based on previous studies examining corporate reputations, including Klein and Leffler (1981), we construct three measures of the intensity of customer reputational sanctions on fraud firms. Our first measure is the likelihood of a break-up in the business relationship between the fraud firm and its large customer after the detection of fraud. We examine this likelihood using a Hazard model to analyze the duration of the relationship as obtained from the firm-large customer match obtained from the COMPUSTAT segment level database.[6] Our second measure is from the perspective of the fraud firm, namely, decreases in fraud firm's sales dependency on its large customers. Our third measure is from the perspective of the customer, namely, decreases in the large customer's cost of goods sold (COGS) attributed to a fraud firm. Throughout the paper, we repeat our analysis using these three measures to ensure robustness of our results.

Our empirical strategy is to calculate these three measures each year and keep track of them over time after the first revelation of the firm's financial misconduct, while searching for any significant changes in customer purchasing policy associated with the fraudulent suppliers' damaged reputation. We are particularly interested in showing that this change in customer behavior is the direct cause of substantial declines in the fraud firm's wealth as found in prior studies. For instance, in our sample of fraud firms, the likelihood of termination of the relationship increases by 5.95% in the year after the detection of fraud and the relationship length is shortened by an average of 0.42 years. In addition, the percent of sales of the fraud firm to the large customer declines by a mean (median) of 4.10% (1.00%) and the percent cost of goods sold to large customers for the firm decreases by a mean (median) of 5.37% (0.03%) after a class action suit is filed. When we convert the aforementioned ratios to a dollar amount, a 1% decrease in the fraud supplier's sales dependency translates to a median loss of $1.23 million in net income. These calculations allow us to compare the estimated dollar costs resulting from these reputational sanctions with the financial penalties imposed by the SEC. Consistent with the prior literature (Karpoff et al., 2005), we find that the reputational costs are large compared to the direct sanctions of the SEC and the Department of Justice (DOJ).

With the help of our three direct measures, we examine several questions related to damaged corporate reputations and customer reputational sanctions. First, we aim to establish the causal relationship between the corporate financial misconduct, customer reputational sanctions, and deteriorating operating performance of the fraud firm.[7] For this purpose, we examine whether significant customer reputational sanctions follow the revelation of financial misconduct by the fraud firm and whether customer reputational sanctions cause a substantial decline in the performance of the fraud firm. Second, we examine whether customers rationally choose the intensity of reputational sanctions by considering the benefits and costs of reputational sanctions. Third, we perform our analysis from the customer's perspective to examine the impact of fraud on a firm's customers. Fourth, we examine whether the reputational losses estimated from the event study approach can be explained by the customer sanctions that result in an increase in firm costs or a decrease in firm revenues.

[3] The foundation of this event study approach is the observation that the decline in shareholder wealth around allegations of fraud tends to far exceed the financial penalties imposed on the firm by the SEC and the DOJ, which is interpreted as evidence of reputational losses resulting from the misconduct. For instance, Karpoff et al. (2005) state that "over 90% of the penalties imposed on firms committing frauds reflect lost reputation."

[4] We define a large customer as any firm that accounts for more than 10% of the fraud firm's sales, consistent with the disclosure requirements of FAS No. 131.

[5] Our choice of large customers of fraud firms as the subject of analysis for studying the product market's reputational sanctions rather than atomistic customers is justified in the previous literature. First, we choose large customers for whom we can exploit the data available in the COMPUSTAT segment level database. Second, Velikonja (2012) suggests that atomistic customers may be less able to impose effective reputational sanctions since naive atomistic customers may fail to implement an optimal response to the fraudulent disclosure. Sophisticated large customers may be better able to avoid this error.

[6] The use of a Hazard model has wide acceptance in the literature in examining time to bankruptcy models (Hillegeist et al., 2004) and time to relationship termination (Fee et al., 2006; Johnson et al., 2013). Our calculation procedure follows that of several studies, including Fee et al. (2006) and Johnson et al. (2013), which utilize relationship termination rates and the percent of firm sales.

[7] We focus on the operating performance of the fraud firms to avoid several problems of the event study methodology, including contamination from reputational effects across firms (Gande and Lewis, 2009) and the ambiguity of the exact date when fraud information becomes public (Karpoff et al., 2012).

To conduct research in this area, the previous studies have used the events of financial misconduct such as SEC sanctions, lawsuits filed by customers, and class action lawsuits. We use class action lawsuits as a useful avenue of inquiry for our investigation for the following reasons.[8] The number of fraud cases involving SEC action is quite small (Kedia and Rajgopal, 2011), so by focusing on class action cases, we are able to expand the sample size substantially. In addition, the corporate misconduct in class action lawsuits runs the gamut of fraud severity, allowing us to examine, at one extreme, cases where the firm is accused of fraud, but the case is ultimately dismissed, and at the other extreme, cases where there is both a class action lawsuit and an SEC action against the firm.

Our empirical results are summarized as follows. First, we find that significant customer reputational sanctions are imposed after the detection of financial misconduct in terms of our three direct measures. Namely, after the detection of a fraud, the fraud firm's trading relationship with its large customer is more likely to break up, its revenue attributable to that large customer decreases, and the large customer's COGS attributable to the fraud firm also decreases substantially. In our multivariate analysis we find that when transaction costs are higher in the fraud firm's industry, when customers can find trading alternatives to the current supplier more easily, and when there is more fraud firm information asymmetry, the customer reputational sanctions are more acute, consistent with Cremers et al. (2008). These results imply that customers rationally choose the intensity of reputational sanctions based on their comparisons between the benefits and costs of reputational sanctions.

Second, we find a significant decline in operating income, net profit margin, and ROA of the fraud firms relative to a control sample. The decline in operating performance is significantly related to our measures of customer reputational sanctions.[9] A fraud firm experiences a larger decline in its operating performance when the firm is particularly dependent upon the large customer and has a higher degree of information asymmetry.

Third, to ensure that our results are not influenced by an omitted variables bias or reverse causality, we employ an instrumental variables approach. Our instrumental variable results strongly support the hypothesis that the decline in the relationship is responsible for at least a part of the decline in the operating performance of the fraud firm.

Fourth, in addition to establishing a causal relationship between the disclosure of the fraud and decline in the operating performance of the fraud firm, we further investigate the mechanism whereby customer reputational sanctions lead to a decline in the operating performance. We find that the selling, general, and administrative costs increase substantially following the revelation of a fraud (by 10.93% in the year after the fraud), consistent with the idea that finding new customers is costly (Klein and Leffler, 1981).[10] In addition, the net profit margin declines by 4.13% and the operating income/assets declines by 2.34%. Our results imply that the decline in the profit margins is the result of the tougher terms of trade by the firm's customers, requiring the fraud firms to increase selling costs to achieve the same level of sales.

Fifth, we find that on the class action filing date and the event trigger date, the fraud firm has a negative and significant cumulative abnormal stock return (CAR). The announcement day return is significantly related to the decline in the fraud firm's operating performance and several measures of customer reputational sanctions, thus supporting the suggestion that reputational losses estimated from the event study approach reflect the reduction in demand for the fraud firm's products by customers. Further, firms with a higher dependence on large customers have a more negative announcement day return. Certain industry characteristics, including the market competitiveness of the fraud firm and the size of transaction costs in the fraud firm's industry are also associated with a more negative announcement day return, consistent with the previous literature (Williamson, 1985).

Sixth, we find that on the class action filing and event trigger dates, the stock price of a fraud firm's customer also has a negative and significant cumulative abnormal return (CAR). This suggests that customers may suffer a real loss due to the purchase of products from a fraudulent supplier, and the real economic decisions of the customers may be distorted by the supplier's fraud (Sadka, 2006). Furthermore, the size of the loss in customer wealth is positively related to the magnitude of reputational sanctions the customer imposes on the fraud firm. This implies that customers likely consider the losses they suffer when they determine the intensity of reputational sanctions. Consistent with this conjecture, we find that the customer's CAR is a significant determinant of the fraud firm's CAR. We find that a 0.05% more negative customer CAR results in a fraud firm's CAR that is more negative by 1%. Since the customers are much larger than the fraud firms, this means that a loss of $1 by the customer is associated with a loss of $1.15 by the fraud firm.[11]

As additional tests and robustness checks, we consider the possibility that our results are driven by some other factors that impair the fraud firm's reputation with other stakeholders. It may be argued that our results are driven by adverse information effects. Perhaps, the financial misconduct, when revealed, coincides with information that the firm's financials are weaker than

[8] We implicitly assume that we can use class action lawsuits for our study of financial misconduct. However, as previous studies (Ferris et al., 2007; Karpoff et al., 2008a, 2008b) suggest, there are a host of violations, the worst of which seems to be financial misrepresentation. We check the details on the types of legal actions in our sample and confirm that the data is suitable for our purpose. We find that most law suits in our sample (81%) are caused by financial misrepresentation.

[9] After the detection of fraud, we find that the firms which terminate the relationship in the first year after the fraud lose 20.4% of their total sales to their large customer. In addition, these fraud firms experience a decline of $16.9 million in net income in the year after the fraud. Of this decline in the operating performance, we estimate that a standard deviation of 1% in the change in percent of sales (−20.7%) results in a decline of 8.8% in operating performance. This figure amounts to a mean loss of $202 million in profits in the year after the fraud.

[10] After the fraud, SG&A/assets increases by a mean (median) amount of 0.10933/10.93% (0.0229/2.29%). An increase of one standard deviation in SG&A is attributed to a 15.25% decrease in ROA. A 1% increase in SG&A results in a decline of −0.45% in ROA. Similarly, an increase of one standard deviation in SG&A is attributed to a 32.7% decrease in the profit margin. A 1% increase in SG&A is attributed to a decline of −0.97% in the profit margin.

[11] This figure comes from the dollar value of a 1% decline in fraud firm's value ($35.873 million) and the associated loss of the large customer in dollar value ($31.094 million). This implies that for each $1 lost by the customer, the fraud firm loses $1.15 (35.8/31.1).

previously believed. This new information about the fraud firm's financial health may cause customers to change the terms with which they are willing to do business with the firm. Alternatively, it may be argued that corporate fraud usually arises at the early stages of financial distress (Alexander, 1999, 2004). We conduct a battery of additional tests to rule out these alternative explanations. Our results suggest that it is the damaged reputation rather than adverse information revealed by fraud detection that causes our documented phenomena. Furthermore, we consider the possibility that our results are caused by an industry shock to both the fraud firm and its large customers. We find that industry-matched firms do not show signs of any such shock, implying that this is not the case. Further, we examine the possibility of our results being caused by the post-fraud adjustment effect documented in Karpoff et al. (2008b). Our results are most consistent with these accounting adjustments being proxies for fraud severity.

Our study contributes to the existing literature in several significant ways. First, we establish the causal link between customer reputational sanctions and loss in the wealth of the fraud firm through an increase in selling costs and a decrease in the revenue of the fraud firm from large customers. Second, we examine the way in which individual stakeholders respond to corporate fraud and check whether these responses are consistent with the predictions in previous studies on corporate reputation. We provide evidence that customers rationally choose the intensity of reputational sanctions, considering the benefits and costs of terminating the trading relationship. Furthermore, to the best of our knowledge, this is the first study providing evidence that the reputational losses estimated by the event study approach reflect the actual deterioration in the trading relationships and increased selling costs for the fraud firms. This finding provides a justification for the large losses in wealth associated with fraud documented in the extant literature, which heavily relies on the event study approach. Finally, we identify large customers, which have direct trading relationships with fraud firms, and analyze the consequences of corporate misconduct from the perspective of the customer.

The rest of the paper is organized as follows. Section 2 explains our hypothesis development. Section 3 describes our methodology and presents the main findings of our study. In Section 4, we discuss our tests for robustness and alternative explanations for our results. Finally, in Section 5, we present our conclusions.

2. Hypothesis development

We approach the hypothesis section by focusing our attention on the sanctions imposed by customers in the product market.

Our first hypothesis is that after the detection of fraud, a customer imposes a reputational sanction that manifests as reduced demand for a fraud firm's products by its customers (Alexander, 1999; Karpoff and Lott, 1993). These sanctions will be discernible in our three direct measures: an increase in the likelihood of a break-up in the relationship, a decrease in the percent of fraud firm's revenues from the large customers, and a decrease in the percent of customer's COGS attributed to the fraud firm.

H1. After a fraud is exposed, customer reputational sanctions will be imposed on the fraud firm in terms of our three direct measures.

Our next hypothesis relates to the determinants of the intensity of customer reputational sanctions. We are interested in seeing whether the intensity of customer reputational sanctions is rationally determined by the customers based on the benefits and costs of the reputational sanctions. We employ variables which previous studies suggest will influence the value of continuing the current supplier–customer relationship (Cremers et al., 2008; Johnson et al., 2013). Thus, these variables will also affect the benefits and costs of customer reputational sanctions, since these sanctions basically consider the deterioration of the trading relationship between the fraud firm and its customer. Customer reputational sanctions will be more acute when the magnitude of fraud is large, when the fraud firm's industry is competitive, and when the fraud firm has high information asymmetry. In the presence of many large potential suppliers that can act as possible trading alternatives, measured by the percentage of firms in an industry serving large customers, a customer is more likely to impose stricter customer reputational sanctions. Likewise, information asymmetry is important since the detection of fraud in case of firms with high information asymmetry will result in a greater surprise to customers, thus, leading the customer to a more drastic revision of the fraud firm's reliability as a trading partner.

H2. Customer reputational sanctions will be more acute when the firm commits a more severe fraud, when there are more alternative suppliers, and when the fraud firm's information asymmetry is higher.

In addition, we propose that customer reputational sanctions are costly to fraud firms, and manifest in the form of a negative effect on a fraud firm's operating performance. Furthermore, if customer reputational sanctions really exist, then the decline in the operating performance of the fraud firm will come through increased selling costs, since the fraud supplier must bear the initial costs to attract new customers (Karpoff, 2010).

H3. After a fraud is exposed, the customer reputational sanctions imposed on a fraud firm will result in a decline in its operating performance. Selling costs will increase substantially after the detection of fraud and this increase will be negatively related to the fraud firm's operating performance.

If customer reputational sanctions are the actual driving force behind the deterioration of the fraud firm's operating performance, then the operating performance of the fraud firm will be negatively related to the factors that increase the customer reputational sanctions in H2.

H4. The same determinants that increase the customer reputational sanctions (more severe fraud, more alternative suppliers, and higher information asymmetry) will lead to a greater decline in the operating performance of the fraud firm after the revelation of fraud.

Previous studies report that fraud firms experience significantly negative first day announcement returns when a fraud is revealed (Karpoff and Lott, 1993; Karpoff et al., 2008b). The previous studies that adopt the event study approach for measuring the reputational losses implicitly assume that the reputational losses estimated from this approach reflect the actual increases in the firm costs or decreases in the revenues. Our direct measures allow us to test this assumption. If a fraud firm's negative CAR comes from customer reputational sanctions, our direct measures of customer reputational sanctions will be significant determinants for the fraud firm's CAR. Furthermore, the aforementioned firm-specific and industry-related variables, which are determinants for the intensity of customer reputational sanctions in H2 and H4, will be significant determinants for the fraud firm's CAR as well.[12]

H5. A fraud firm's negative announcement day return on the detection of fraud will be directly related to our direct measures of customer reputational sanctions. Further, determinants that are associated with increased customer reputational sanctions (more severe fraud, more alternative suppliers, and higher information asymmetry) will lead to a greater decline in the fraud firm's announcement day returns.

After a fraud is revealed, the market realizes that customers will have to bear several costs coming from the supplier fraud (Alexander, 1999). Furthermore, when customers impose product market sanctions, customers as well as their suppliers incur certain costs due to the termination of business relationships. The aforementioned arguments suggest that the customers will also experience a negative CAR upon the disclosure of a supplier fraud. Further, the customer's CAR will be positively related to the fraud firm's CAR. Determinants for the reputational sanctions will make the customer's CAR more negative since the costs of terminating the current trading relationship as a result of reputational sanctions may manifest as part of the customer's negative announcement return. This leads to the following hypothesis[13]:

H6. The customer of a fraud firm will experience a significantly negative announcement day return upon the detection of fraud. The determinants that increase customer reputational sanctions (more severe fraud, more alternative suppliers, and higher information asymmetry) will lead to a greater decline in the customer firm's announcement day returns.

3. Methodology, results, and discussion

3.1. Sample selection

Our sample begins with N = 2645 class action files from 1996 to 2009, obtained from the Stanford Law School Securities Class Action Clearinghouse. The advantage of this dataset is that all the suits are filed under SEC rule 10b-5, thus, providing some consistency in the sample. This SEC rule prohibits any untrue or misleading statement as well as the omission of any material information needed for the interpretation of the statements. For each lawsuit, we collect information about the outcome of the case, that is, whether the case is settled or dismissed. A case is classified as dismissed if it is recorded explicitly as dismissed by the judge or the case is classified as voluntarily dropped by the plaintiff in the case description or civil docket. In addition, we collect information about the size of the fraud allegation,[14] and the date when the fraud is filed in Federal court.

We then merge the class action firms with the COMPUSTAT segment level data to collect firms with large public customers in the year when the lawsuit is filed.[15] The COMPUSTAT segment level data contains information that the firms are required by regulation to disclose about the level of sales from all customers accounting for greater than 10% of total firm sales. We then use the information disclosed in the segment level data to determine if the large customers are publicly traded in the year of the class action filing.[16] We eliminate observations where the firm has been the defendant in a class action filing within the last five years.[17] Finally, we require the firms to have annual reports available in the SEC's EDGAR database in the year of the fraud. This yields a sample of N = 168 firms with a class action filing that also have a large public customer in the same year.

[12] An alternative explanation yields the same prediction. Suppose customers see a large market reaction as an indication that the end results of the legal battles are detrimental to the fraud firm and the customer (as was the case for asbestos producers). Clearly, this is different from the situation where the market reacts negatively because the customer actions would have long-term adverse implications for the firm. We will examine this issue later in Section 3.4.

[13] Even though we find evidence on the effect of fraud detection on the loss of value of the customer, this finding may not be a result of the product market effect as is argued in H5. It is also possible that since the customers are large firms and may have many resources available (i.e., deep pockets), the customer may be subjected to a secondary wave of lawsuit. This legal action may be pursued since the customers under the legal action should have known that their suppliers were involved in financial misconduct. We address this so called “deep pockets argument” in Section 4.5 of the paper.

[14] We use the resolution amount as a proxy for the fraud size, which is the aggregate compensation amount paid by the defendant to the plaintiff for the settled cases, collected from the case description document or the original civil docket.

[15] The COMPUSTAT segment level database is utilized by Fee et al. (2006), Hertzel et al. (2008), and Johnson et al. (2010).

[16] We use the large customer name and other information disclosed in the firm annual reports to determine the identity of the large customers. Details of a similar process are described in detail by Fee and Thomas (2004).

[17] Elimination of all the firms with prior class action filings allows us to consider the class action lawsuits as independent observations. This elimination does not introduce a look-ahead bias since we only eliminate the observations if there has been a filing within the last five years.

For each firm with a class action suit and a large customer according to their financial filings, we collect detailed information about the relationship between the firm and its large customer. This information includes the percent of sales, the history of the relationship with the customer, and the future relationship performance in terms of the percent of sales and the percent of cost of goods sold to the customer.

One important component of our study is the selection of a control group of matching firms for empirical comparison with the fraud firms. We select a group of firms in the same two-digit SIC code classification as the class action firms so that we might control for industry-specific effects.[18] Since we are particularly interested in the impact of fraud on the customer–supplier relationship, we select our matching firms from the universe of firms with large customers based on their disclosure in the COMPUSTAT segment level data. We sort each fraud firm by industry and fiscal year into a portfolio of other firms with +/−50% of total assets of the fraud firm. We then identify the firm in the portfolio with the ROA closest to the fraud firm in the year before the fraud. For the fraud firms that cannot be matched based on this criterion, we sort the firms by industry, year, and −75%/+150% of the firm's assets. We then match the firm with the ROA closest to the fraud firm. This yields a sample of 168 firms having a class action suit filed against them and a matching group of 168 firms from the same industry and with similar firm size and profitability.

For each firm subjected to a class action lawsuit, we examine the Stanford Clearinghouse documents to determine if there is a trigger event for the class action. There is often no explicit trigger event stated in the Stanford Clearinghouse, so we look for relevant news events in the class action filing as well as LexisNexis from the beginning of the class action to the filing period to find a trigger event not listed in the Stanford Clearinghouse. We find that 64.8% of the firms in the class action database have an explicit event that led to the filing of the class action lawsuit. Karpoff et al. (2008b) similarly find that 63.4% of the SEC enforcement actions have a trigger event.

3.2. Key measures of customer reputational sanctions

A major innovation of our paper is the use of direct measures of customer reputational sanctions based on the theoretical suggestion of how individual customers respond to the firm's fraud (Alexander, 2004; Klein and Leffler, 1981). We focus on three measures: the hazard rate of the relationship terminating,[19] the change in the percent of sales made to the large customer by the fraud firm, and the change in the percent cost of goods sold purchased by the customer. To generate these direct measures, we utilize the COMPUSTAT segment level data for each year the relationship exists. We then examine the years subsequent to the fraud to determine the first time the relationship is not disclosed, coding this as the year when the relationship terminates.[20] This provides a useful measure for the relationship termination. In addition, we collect the number of years the relationship was disclosed prior to the fraud as a measure of the pre-fraud relationship durability. However, because survival data is not normally distributed, the literature has largely focused on utilizing a Hazard model to examine the rate of relationship termination. This leads us to our first measure of relationship sanctions, the hazard rate where:

$$\text{hazard rate}(t) = \lim_{\Delta t = 0} \frac{\Pr[(t \le T < t + \Delta t) | T \ge t]}{\Delta t}$$

where t is a point in time, T is the time of a termination and Δt is a small incremental period of time.

In addition, for each fraud firm–customer relationship, we collect the dollar value of sales from the fraud firm to the customer. We then divide the sales to the customer by the total sales of the fraud firm to calculate the percent of sales in the years around the fraud event. This leads us to our second measure, the change in the fraud supplier's sales dependency:

$$\text{Change in percent sales} = \left(\text{sales to customer}_{t=+1}/\text{total sales}_{t=+1}\right) - \left(\text{sales to customer}_{t=-1}/\text{total sales}_{t=-1}\right).$$

Further, we utilize the sales to the fraud firm's customer divided by the cost of goods sold by the customer. This measure is useful since it allows us to examine the changes in purchasing patterns of the customer around the fraud event. This leads to our third measure, the change in the customer's percent COGS related to purchases from the fraud supplier each year:

$$\text{Change in percent COGS} = \left(\text{sales to customer}_{t=+1}/\text{total COGS}_{t=+1}\right) - \left(\text{sales to customer}_{t=-1}/\text{total COGS}_{t=-1}\right).$$

[18] By using control firms in the same industry as the fraud firms, we are able to eliminate the impact of industry spillover (Gande and Lewis, 2009) and focus on the impact of the fraud itself on the relationship. Our results show that the industry effect documented by Gande and Lewis (2009) is not driving our results, and we find an independent effect of customers imposing a reputational penalty on firms that commit fraud.

[19] The hazard rate is the number of relationship terminations per unit time t as the time interval approaches zero. A higher hazard rate means that the relationship is more likely to terminate.

[20] Our measure for relationship termination follows Fee et al. (2006) and Johnson et al. (2013). In robustness tests, we repeat our analyses to determine if our results change appreciably by classifying a terminated relationship as one that shows a drop below 15% or 20% in sales, but find no significant change in our results. Our robustness section discusses the termination of relationships in more detail.

Table 1
Fraud characteristics.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. Cases are classified as dismissed if they are explicitly recorded as dismissed by a judge or voluntarily dropped by the plaintiff in the case description or civil docket. Cases are classified as involving fraudulent disclosure if the fraud is filed as a 13(b) violation or the suit explicitly mentions fraudulent disclosure. The compensation requested is the aggregate dollar amount explicitly requested in the class action filing. The resolution amount is the aggregate compensation amount the defendant paid to the plaintiff for the settled cases, as retrieved from the case description or civil docket.

Legal sanctions				
	N	Mean	Median	Standard deviation
Fraud dismissed (indicator)	168	0.36	0.00	0.48
Financial misrepresentation (indicator)	168	0.81	1.00	0.48
Compensation requested ($ millions)	97	264.13	16.40	1079.72
Resolution amount ($ millions)	57	28.70	6.00	84.14

3.3. Fraud and firm characteristics

We begin with a discussion of the fraud characteristics of the firms in our sample as reported in Table 1. We find that 36% of the lawsuits against the firms in our sample are dismissed by the court. In our sample, we observed that a majority of the lawsuits (81%) specifically accuse the firms of financial misrepresentation.[21] According to our findings, a subset of the sample (N = 97) explicitly mentions the requested compensation in the lawsuit, and the mean (median) compensation requested is $264 million ($16 million). For a subset (N = 57) of the suits where we can find the actual settlement amount (not dismissed and not still pending), the mean (median) settlement amount is $29 million ($6 million). These figures are quite close to the class action settlements reported by Karpoff et al. (2008b), where the mean (median) settlement amount is $38 ($1) million.[22]

In Table 2 we present the characteristics of our sample of fraud and matching firms. As previously discussed, each fraud firm with a large customer is matched to another firm with a large customer based on industry, size, and profitability following Loughran and Ritter (1997). We find that the median assets of fraud firms are $292 million and the median assets of the matching firms are $222 million. These results are insignificantly different, which is not surprising since one of our matching criteria is firm size. We find that the median fraud (matching) firm's leverage is 0.15 (0.13), median firm age is 7 years (9 years), and median Tobin's Q is 1.53 (1.48). None of the differences in leverage, age, or Tobin's Q for the fraud firms versus the matching firms are statistically significant. We do find that the fraud firms have a significantly higher market capitalization of $345 million compared to a market capitalization of $259 million for the matching firms. Examining the industry characteristics, we find that 22% of the firms in the same industry as the fraud firms (and the respective matching firms) have large customers, indicating that relationships are fairly important in these industries.[23]

One benefit of matching the fraud firms with large customers to non-fraud firms with large customers is that it allows us to compare the customers of the two sets of firms. We find that the median total assets, leverage, and Tobin's Q for the customers of the fraud firm (matching firm) are $25 billion, 0.19, and 1.66, respectively ($26 billion, 0.18, and 1.63, respectively). None of the differences are statistically significant indicating that the firms are very similar to each other. We also find that the median market capitalization of the fraud firm customers (matching firm customers) is $25 billion ($27 billion).

Also important in our analyses are the characteristics of the relationship between the fraud firm and its customer. We find that the median percent of firm sales (sales to large customer/total firm sales) of fraud (matching) firms to their customers is 17% (19%). The difference between the fraud firms and the matching firms is insignificant implying a good match between the two sets of firms. We do find a significant difference in the median percent of customer cost of goods sold (sales to large customer/total customer cost of goods sold) between the fraud firms (0.32%) and the matching firms (0.64%). Although this is not a major measure used in this study, it may be an artifact of the highly skewed nature of the percent of cost of goods sold. We find that fraud firms have a slightly longer median relationship time than the matching firms as the duration of relationship of the fraud firm with its customer before the fraud is found to be two years compared to the one-year relationship time of the matching firm, however, this difference is not significant. These results suggest that the matching firms are well suited as a control sample since their firm characteristics, customer characteristics, and relationship characteristics are similar to the fraud firms.

[21] We find that of the firms not accused of financial misrepresentation, N = 29 are accused of not disclosing relationships appropriately in the process of their initial public offering. Another two firms are accused of not disclosing relationships associated with their consummation of a merger.
[22] In addition, we examine the class action filings as well as LexisNexis to determine if our firms are subject to government enforcement actions by the SEC or the Department of Justice. We find that only 16 (9.52%) of our firms are under investigation at the time of the class action filing. Our major results are robust to elimination of these 16 firms from our sample.
[23] Johnson et al. (2010) find that IPO firms have large customers 73% of the time. Our results have a significantly smaller percentage of firms with large customers, since in contrast to IPO firms, our sample is not dominated by technology firms.

Table 2
Summary statistics.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. Matching firms are selected from the universe of firms disclosing large public customers, based on the COMPUSTAT segment level database. We select a firm as the matching firm if it is in the same two digit sic code within +50% or −50% of assets in the year before the fraud, matched based on the return on assets in the year before the fraud. For firms without a match based on these restrictions, we rematch the firms using a +150% or −75% restriction on assets and based on industry and return on assets in the year before the fraud. Total assets is COMPUSTAT item *at* and firm market capitalization is prcc_f*csho. Leverage is long term debt + debt in current liabilities/firm assets. Firm age is the time from the first year the assets are available in COMPUSTAT until the year of the fraud. Q is COMPUSTAT data item (at-ceq + prcc_f*csho)/at. The same industry as customer is an indicator variable that takes a value of one if the fraud firm and its large customer are in the same two digit SIC code industry based on COMPUSTAT. * and ** signify that differences measured by *t*-test and Wilcoxon test are significant at the 10% and 5% levels, respectively.

Variable	N	Fraud firms (N = 168)	N	Matching firms (N = 168)	*z*-Test
		Median		Median	
Firm characteristics					
Total assets ($ millions)	168	292.37	168	221.93	1.62
Leverage	168	0.1543	168	0.1262	0.81
Firm age (years)	168	7.00	168	9.00	1.08
Q	168	1.53	168	1.48	1.19
Market capitalization ($ millions)	168	344.67	168	258.93	2.27**
Industry characteristics					
Percent of firms with large customer	168	0.2154	168	0.2154	0.00
Customer characteristics					
Total assets ($ millions)	168	24,861	168	25,539	0.08
Leverage (long term debt/total assets)	168	0.1863	168	0.1826	0.08
Q	168	1.66	168	1.63	0.08
Market capitalization ($ millions)	168	24,980	168	26,548	0.44
Customer–supplier relationship characteristics					
Percent of supplier's total sales to customer	168	17.45%	168	19.47%	0.95
Percent of customer's cost of goods sold to customer	168	0.32%	168	0.64%	2.39**
Pre-lawsuit relationship length (years)	168	2.00	168	1.00	1.16

3.4. Existence of customer reputational sanctions following fraud as shown by three direct measures

We now turn our attention to the changes in our three key measures of customer reputational sanctions. Since fraudulent activities at supplier firms change the incentives of customers to continue with the relationships with their suppliers, we expect to see significant differences between the fraud firms and the matching firms after the detection of fraud.

In Table 3 Panel A and Panel B, we report the changes in the relationships from the year before the fraud to the various years after the fraud event for the fraud and matching firms, respectively. We find, for instance, that from the year before the fraud (−1) to the year of the fraud (0), 24% of the fraud firms and 20% of the matching firms terminate the relationship.[24] We find that as we move out to years +3 and +4, the fraud firms have significantly higher termination rates at 80% and 87%, respectively, as compared to the matching firms which have termination rates of 73% and 79%, respectively. Table 3 Panel C reports the *z*-statistics for the Wilcoxon test comparing the two samples of firms. One difficulty with the analysis of relationship terminations is that they are not normally distributed making a Hazard model more amenable to examine this measure of relationships. We address this issue in the next section (Tables 4 and 5).

We also find in Table 3 Panel A and Panel B that the fraud firms have a significantly larger decline in the total percent of firm sales to the large customers compared to the matching firms. For instance, we find that from year (−1) to year (+1), the fraud firms have a decline of 1% in their sales to the large customer whereas the matching firms have an increase of 2% in their sales to the large customer. This difference is significant at the 1% level. These results are consistent throughout Table 3, with fraud firms always showing a significantly larger decline in the percent of sales to their large customers in all years after the fraud compared to the matching firms.

Finally, we examine the percent cost of goods sold for the customers of the fraud firms and find qualitatively similar results. We find that the cost of goods sold attributed to the fraud firm's customer has a marginally significant decline of −0.02%, compared to an increase in the percent cost of goods sold of 0.01% for the matching firms' customers from year (−1) to year

[24] This result is qualitatively similar to the findings of Fee et al. (2006) which finds that the 25th percentile of the relationship length is 1 year, implying that 25% of firms terminate their customer–supplier relationships within one year. In addition, the management literature (Ring and van de Ven, 1994) and the supply chain literature (Wagner, 2011) both show that there are many reasons for the termination of supplier–customer relationship. The reasons could be exogenous, such as technology changes, natural disasters, or political effects. It is also possible that the termination is a result of endogenous reasons, such as a shift in organizational commitments, completion of a business deal such as a merger (Fee and Thomas, 2004), or simply due to a falling out among parties.

Table 3
Evidence on the existence of customer reputational sanctions in terms of three direct measures.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify the customers as public or non-public. This yields N = 168 firms in the database with a large public customer. Matching firms are selected from the universe of firms that disclose large public customers based on the COMPUSTAT segment level database. We select a firm as the matching firm if it is in the same two digit SIC code within +50% or −50% of assets in the year before the fraud, matched based on the return on assets in the year before the fraud. For firms without a match based on these restrictions, we rematch using a +150% or −75% restriction on assets and based on industry and return on assets in the year before the fraud. Percent of sales to largest customer is the sales to the largest customer divided by the total firm sales. Cumulative percent terminating relationship is the percent of firms that terminate relationships within the specified time period. In panel 3, p-values for the *z*-statistics of Wilcoxon signed rank tests are reported in brackets. *, **, and *** signify a significant difference from zero in Wilcoxon signed rank tests at the 10%, 5%, and 1% levels, respectively.

Change in performance	Cumulative percent terminating relationships	Percent of sales to largest customer	Percent customer cost of goods sold
Panel A. Changes in relationship for fraud firms, median values			
Year −1 to 0	0.2440	−0.03%	−0.02%
Year −1 to 1	0.4762	−1.00%	−0.03%
Year −1 to 2	0.6726	−1.00%	−0.02%
Year −1 to 3	0.8036	−3.00%	−0.02%
Year −1 to 4	0.8690	−2.00%	0.01%
Panel B. Matching firms matched based on industry, size, and ROA			
Year −1 to 0	0.2024	1.00%	0.00%
Year −1 to 1	0.4167	1.67%	0.01%
Year −1 to 2	0.5952	2.06%	0.00%
Year −1 to 3	0.7262	0.72%	0.03%
Year −1 to 4	0.7917	0.52%	0.04%
Panel C. Wilcoxon test of significance of difference, fraud firms − matching firms			
Year −1 to 0	0.92	3.57***	1.61*
	(0.36)	(0.00)	(0.10)
Year −1 to 1	1.10	3.39***	2.09**
	(0.27)	(0.00)	(0.04)
Year −1 to 2	1.47	1.91*	1.94*
	(0.14)	(0.06)	(0.05)
Year −1 to 3	1.67*	2.01**	1.11
	(0.09)	(0.04)	(0.27)
Year −1 to 4	1.89*	2.13**	0.27
	(0.06)	(0.03)	(0.79)

(+1). This difference is significant at the 5% level. Overall, the results in our study show that the fraud firms exhibit a significant decline in all the examined relationship-specific variables in terms of our three direct measures. We now move on to a multivariate regression framework to examine the fraud, industry, and firm characteristics that may help to explain this decline in the relationship.

In Table 4 Panel A, we report the results of a multivariate Hazard model regression using a Cox model specification, following Fee et al. (2006) and Johnson et al. (2013).[25] We find consistent results using a Weibull distribution, but prefer the non-parametric Cox specification for our tabulation.[26] To provide a measure of explained heterogeneity, we consider the discussion in Heller (2012) and report the pseudo-R^2 in all Hazard model regressions in Tables 4 and 5.

In Table 4 Panel A models (1) through (4), we specifically examine the effects of the legal penalties on the customer reputational sanctions. We wish to determine if the size of the fraud is related to the customer reputational sanctions, with more severe frauds resulting in the imposition of larger reputational sanctions by the customers. As previously discussed, a dismissed case may be frivolous and therefore, the customers may be inclined to impose a less severe sanction on the firm. This is consistent with the significant coefficient below one reported in model (1) for dismissed frauds. In models (2)–(4), we find that frauds of a more severe nature, as measured by those involving financial misrepresentation, and those involving a higher compensation requested by litigating parties, have a significantly higher hazard rate. We find that the relationship between the hazard rate and the resolution amount of the fraud is not statistically significant.

Certain industry characteristics may also make the sanctions imposed by the customers more severe. Specifically, in Table 4 Panel A models (5) and (6), we examine the supplier industries with high levels of competition, as measured by above the median industry Herfindahl index and the industry percentage of firms with large customers. As suggested in Cremers et al. (2008), supplier industries with high levels of competition may indicate that there are many trading alternatives available to the customers to replace the current supplier, which will intensify the customer reputational sanctions. Consistent with this

[25] We include all the control variables from the prior studies except for the percent of firm sales or the percent of firm sales^2. Adding the additional controls does not significantly change our results. In addition, we add industry and year indicator variables as well as control variables for situations where the fraud firm and its customer are in the same industry, since industry spillover effects may cause contamination of the customer performance.

[26] In the Hazard model, a coefficient above one is interpreted as an increase in the hazard rate (making the relationship more likely to terminate), and a coefficient below one is interpreted as a decrease in the hazard rate (making the relationship less likely to terminate).

Table 4
Hazard model and choice model examining the likelihood of relationship breakup.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. In Panel A, the dependent variable is the hazard rate of relationship termination. In Panel B, the dependent variable is an indicator variable taking a value of one in the year the relationship terminates. Panel B is a panel dataset where each observation is one year that the relationship survives. Standard errors clustered by industry are reported below the coefficients. All regressions include control variables of log(1 + firm age), the relationship history, the fraud firm market capitalization, Tobin's Q, fraud firm leverage, and an indicator variable taking a value of one if the fraud firm and its customer are in the same industry, and zero otherwise. *, **, and *** signify significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Hazard model using Cox specification									
Size of legal sanctions									
Dismissed case (indicator)	0.680*								
	(0.161)								
Financial misrepresentation (indicator)		1.545*							
		(0.361)							
Compensation requested ($ millions)			1.035***						
			(0.013)						
Resolution amount ($ millions)				0.996					
				(0.003)					
Industry characteristics									
High competition industry (indicator)					6.118***				
					(2.906)				
Percent of firms serving large customers						0.178			
						(0.862)			
Information asymmetry									
Stock return volatility							2.871**		
							(1.369)		
Analyst coverage (indicator)								0.637***	
								(0.111)	
Bargaining power									
Percent of fraud firm sales to customer									1.684**
									(0.447)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168	168	98	57	168	168	168	168	168
Pseudo-R^2	3.58	3.67	5.66	9.24	3.42	3.42	3.54	3.57	3.45
Panel B. Logistic choice model									
Size of legal sanctions									
Dismissed case (indicator)	−0.362								
	(0.305)								
Financial misrepresentation (indicator)		0.440*							
		(0.258)							
Compensation requested ($ millions)			0.031**						
			(0.015)						
Resolution amount ($ millions)				−0.008***					
				(0.002)					
Industry characteristics									
High competition industry (indicator)					0.059				
					(0.137)				
Percent of firms serving large customers						6.353			
						(8.687)			
Information asymmetry									
Stock return volatility							2.358***		
							(0.601)		
Analyst coverage (indicator)								−0.459***	
								(0.178)	
Bargaining power									
Percent of fraud firm sales to customer									0.048
									(0.213)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	479	479	280	166	479	479	479	479	479
Pseudo-R^2	0.08	0.08	0.10	0.16	0.07	0.07	0.07	0.08	0.07

Table 5
Hazard model and choice model examining the likelihood of relationship breakup controlling for endogeneity.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. The dependent variable is an indicator variable taking a value of one in the year the relationship terminates. The data is a panel dataset where each observation represents the year that the relationship survives. Standard errors clustered by industry are reported below the coefficients. All regressions include control variables of log(1 + firm age), the relationship history, the fraud firm market capitalization, Tobin's Q, fraud firm leverage, and an indicator variable taking a value of one if the fraud firm and its customer are in the same industry and zero otherwise. *, **, and *** signify significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Hazard model using Cox specification	OLS	Stage 1	Stage 2
		Dependent variable = relationship termination (indicator)	Dependent variable = fraud indicator	Dependent variable = relationship termination (indicator)
Endogenous variables				
Fraud firm	1.544**	0.101**		
(indicator)	(0.184)	(0.043)		
Fraud firm				2.881***
(instrumented variable)				(1.030)
Instrumental variables				
Percent of firms with class action			0.120***	
lawsuit in state			(0.042)	
Control variables	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes
N	336	954	954	954
Pseudo-R^2/R^2	2.03	14.29	82.53	14.32

conjecture, we find in particular that highly concentrated industries have a significantly higher hazard rate as reported in model (5). We also examine the impact of information asymmetry on the hazard rate of the relationship between the fraud firms and their large customers. We find that higher information asymmetry, as measured by stock volatility (model (7)) and a lack of analyst coverage (model (8)) both result in a higher hazard rate, implying that the information asymmetry exacerbates the relationship between the fraud firm and its large customers. Finally, in model (9) we examine a proxy for the supplier dependency on its large customer and find that the more a supplier is dependent on its customer (as measured by the percent of sales to the large customer), the more likely the relationship is to break up due to customer reputational sanctions. Thus, variables that influence the value of a continuing supplier–customer relationship and the probability of the customer leaving the relationship help to explain the intensity of customer reputational sanctions.

To ensure that our results are not driven by the specification of our Hazard model, we repeat our analyses using a Choice model. We follow Fee et al. (2006) in first creating a panel of observations for each year that the relationship with the large customer survives. We then create an indicator variable for the year the customer chooses to terminate its relationship with the fraud firm. For every year that the relationship continues, the indicator variable takes a value of zero, but in the year of relationship termination, the variable takes a value of one. We then run a Choice model logistic regression, where the logit allows us to determine the impact of the size of the legal sanction, the industry characteristics, the information asymmetry, or the bargaining power on the probability of relationship termination.

We tabulate our Choice model results from the logistic regression in Table 4 Panel B. We find that our results are qualitatively similar to the Hazard model results in Table 4 Panel A, with only a few exceptions. First, the variables for dismissed lawsuits, high competition industry, and the percent of sales are not significant in the Choice model regression. However, we find that the resolution amount becomes significant in the Choice model regression. Overall, the Choice model shows that our results are not dependent upon the Hazard model specification, but results consistent using the two methods.

Next we examine the relationship between fraud and relationship termination by comparing fraud firms with a set of control firms. We combine our fraud firms with our control firms to see the actual impact of fraud on the relationship termination. We begin by running a baseline Hazard model regression using a Cox specification in Table 5 model (1). By including both, the fraud firms and the control firms, we can determine the marginal impact of fraud on the hazard rate of the firms. We find that the firms that commit fraud are in fact more likely to have their relationships end, compared to firms that do not commit fraud. We then set up a panel dataset to run a Choice model for the fraud firms and control firms in the same way as in Table 4 Panel B. We find in an OLS regression (Table 5 model (2)) that there is positive and significant relationship between a firm committing fraud and the termination of relationship with the customer. This result is consistent with our prior results, indicating that when a firm commits fraud, its customers impose sanctions on the firm by terminating the relationships.

However, one important issue of our empirical analysis is the fact that frauds are not exogenous events; rather, they are controlled by managers. We therefore use a Choice model to control for the endogeneity in the fraud of the firms using an instrumental variables approach: two-stage least squares regression (2SLS) in Table 5 models (3) and (4).[27] We search through the related literature to find a potential instrument correlated with fraud that will not be correlated with the residual from a regression examining changes in operating performance. We find in the economics literature that agents in close proximity with each other are more likely to imitate the behaviors of others with whom they have regular interaction (Glaeser et al., 1996). This effect should include behaviors such as financial misconduct. We therefore propose that after controlling for industry effects, firms located close to other firms that commit fraud are more likely to commit fraud. This instrument should not be correlated with operating performance except through the presence of fraud once we control for industry effects, making it a good instrumental variable for our purposes. Therefore, we use as an instrument the percent of firms located in the same state as the fraud firm which also have a listed class action lawsuit against them in the year before the class action suit against the fraud firms in the sample.

We find in Table 5 model (3) that belonging to an industry where many other firms are accused of fraud correlates with committal of fraud by firms with a coefficient of 0.12, significant at the 1% level. Our second stage regression in Table 5 model (4) shows that after controlling for the endogeneity of the fraud relationship, the relationship is still more likely to terminate after the fraud, consistent with the customers imposing sanctions on the firm in response to the fraud. To confirm that the percent of firms in the home state in the year of the fraud that are also in the class action database is not a weak instrument, we run a Kleibergen–Papp test and find the F-statistic to be 8.16 (Cruz and Moreira, 2005). This value is marginally larger than the Stock and Yogo (2005) critical values, implying that the instrumental variable is not a weak instrument.

Since we are interested in multiple measures of customer reputational sanctions, we now move on to examine the change in our second measure, namely the percent of firm sales to large customers. Table 3 shows a substantial decline in the percent of sales after a fraud, relative to a set of matched firms. We now utilize a multivariate OLS regression setup to examine the changes in the percent of sales from year (-1) to year ($+1$) around the fraud.[28] We use similar control variables as in the prior tables, although we omit log($1 +$ firm age) from the control variables. We find no sensitivity to the inclusion of this control in our regressions. It should be noted that our sample is smaller ($N = 114$), since in this multivariate OLS regression, the firm must have the percentage of firm sales to the large customer available in year (-1) and year ($+1$) to be included in the sample. Any firm terminating its relationship before year ($+1$) cannot have the change in percentage sales measured, and is thus, not in the regression. As such, fraud firms with the most severe sanctions from their large customers are not included in the sample. This reduced sample size and bias toward firms whose relationships survive to year ($+1$) reduces the power of the regressions in Table 6. The results obtained in Table 6, models (1)–(9), are similar to model (1)–(9) in Table 4 in terms of qualitative directions and statistical significance. In model (9), we may interpret the percent of sales to the large customer as a measure of the bargaining power of the fraud firm. When the fraud firm has very weak bargaining power, then customers may take advantage of the fraud firm's weak bargaining power and impose terms of trading on the fraud firm that are more favorable to them. Therefore, the trading relationships between the fraud firm and the customer may last longer. However, we predict that the fraud firm's weak bargaining power will cause a greater deterioration in the fraud firm's performance and further decrease its announcement return upon the detection of fraud.[29]

In addition, we consider the possibility that the fraud may be endogenous, which means that estimates from Table 6 models (1)–(9) are inconsistent. To test whether fraud firms have larger declines in percent of sales to their customers compared to matching firms, we first combine the fraud firms and large customers into panel of data, as in Table 5. In Table 6 model (10) we run an OLS regression and we find that fraud firms do in fact have a significantly larger decline in percent of sales compared to the control group. To control for possible endogeneity, we use a 2SLS regression setup as in Table 5, utilizing the percent of firms with a class action lawsuit in the same state as the fraud firm as an instrumental variable. To avoid multicollinearity problems in our second-stage regression, we only use year indicator variables in the first-stage regression, as suggested by Cliff and Denis (2004). We find that the first-stage regression results in a positive and significant relationship between the percent of firms in the same state as the firms committing fraud, and a firm committing fraud (not tabulated). These results are not surprising as they are analogous to the first-stage regression results in Table 5 model (3). In the second stage regression, we find that the fraud firms have a larger decline in the percent of sales to their customers, even after controlling for the endogeneity of the fraud event (Table 6 model (11)). This implies that the fraud actually results in a decline in percent of sales to the large customer and our OLS results are not an artifact of endogeneity.

Thus far, we have shown that subsequent to a fraud detection, a firm's relationship with its large customers decays substantially. We now examine the operating performance of the fraud firms to see if this relationship change is costly to the fraud firm in terms of having an adverse impact on their subsequent operating performance.

[27] It is important to note that as we are utilizing a 2SLS regression model, we assume that a linear probability model will estimate the second stage regression in an unbiased manner. Our paper is not the first to use a 2SLS procedure to control for fraud endogeneity (Chen et al., 2006).

[28] We focus on the change in percent of sales from year -1 to $+1$ to ensure that the full effect of the fraud is manifested in the sales performance of the fraud firm. If a fraud occurs near the end of a fiscal year, the impact of the fraud on the firm may be negligible since the customers cannot likely adjust their purchasing policy in less than one quarter.

[29] While we also consider the change in percent cost of goods sold as a dependent variable in the tests, we do not tabulate these results.

Table 6
Regression results for change in percent of firm's sales from year −1 to year +1 around the fraud event.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. The regression model is the hazard rate for the fraud firms estimated using a Cox proportional hazards model. The sample size is 114 as change of sales is missing for firms that had terminated relationships within year +1. Standard errors for OLS regressions clustered by industry are reported below the coefficients. All regressions include control variables of log(1 + firm age), the relationship history, the fraud firm market capitalization, Tobin's Q, fraud firm leverage, and an indicator variable taking a value of one if the fraud firm and its customer are in the same industry and zero otherwise. *, **, and *** signify significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	2SLS
Size of legal sanctions											
Dismissed case (indicator)	0.064*										
	(0.036)										
Financial misrepresentation (indicator)		−0.071*									
		(0.039)									
Compensation requested ($ millions)			−0.006*								
			(0.003)								
Resolution amount ($ millions)				−0.003							
				(0.007)							
Industry characteristics											
High competition industry (indicator)					−0.030						
					(0.137)						
Percent of firms serving large customers						−2.544*					
						(1.266)					
Information asymmetry											
Stock return volatility							0.0178				
							(0.254)				
Analyst coverage (indicator)								−0.027			
								(0.097)			
Bargaining power											
Percent of fraud firm sales to customer									−0.173		
									(0.283)		
Endogenous variables											
Fraud firm (indicator)										−0.096*	
										(0.051)	
Fraud firm (instrumented variable)											−0.256*
											(0.50)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	114	114	70	37	114	114	114	114	114	218	218
Pseudo-R^2	27.93	28.20	23.78	90.15	26.43	30.83	26.71	26.63	28.13	19.62	8.56

3.5. Changes in operating performance

3.5.1. Changes in operating performance of the fraud firms relative to matching firms

We begin by examining several measures of changes in the operating performance of the fraud firms, including changes in ROA (net income/total assets), profit margin (net income/sales), OIBD/assets (operating income before depreciation/total assets), and OIBD/sales (operating income before depreciation/sales). All the four measures in Table 7 Panel A show a decline in the operating performance of the fraud firms. For instance, the fraud firm's ROA declines by 4.8% from year (−1) to year (0), and by 5.8% from year (−1) to year (+1). When we compare these values for the matching firms, we find that the matching firms also exhibit a decline in the operating performance after the fraud event. This result is consistent with Maksimovic and Titman (1991), who claim that frauds will precede a decline in future earnings. However, the decline in the earnings seems to be industry-specific to some extent and not just firm specific, as shown in Table 7 Panel B. We find, for instance, that the decline in ROA of the matching firms is 2.1% from year −1 to year 0, and 1.1% from year −1 to year +1.

In Table 7 Panel C, we examine the statistical significance between the changes in the operating performance of the fraud and matching firms. We consistently find that the decline in the operating performance of the fraud firms after the fraud is significantly more negative compared to the matching firms, suggesting that these results are not entirely driven by an industry effect.[30]

[30] In Internet Appendix Table A.1, we show that the decline in the operating performance is also significantly more negative than the industry median changes.

Table 7
Fraud firm's operating performance around the fraud events.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. Matching firms are selected from the universe of firms that disclose large public customers based on the COMPUSTAT segment level database. We select a firm as the matching firm if it is in the same two digit SIC code within +50% or −50% of assets in the year before the fraud, matched based on the return on assets in the year before the fraud. For firms without a match based on these restrictions, we rematch using a +150% or −75% restriction on assets and based on industry and return on assets in the year before the fraud. Percent of sales to largest customer is the sales to the largest customer divided by the total firm sales. OIBD/assets is firm's operating income before depreciation divided by total assets, OIBD/sales is firm's operating performance before depreciation/assets, ROA is net income divided by assets, and profit margin is net income divided by sales. *, **, and *** signify a significant difference from zero in Wilcoxon signed rank tests at the 10%, 5%, and 1% levels, respectively.

Change in performance	ROA	Profit margin	OIBD/assets	OIBD/sales
Panel A. Fraud firm changes in operating performance, median values				
Year −1 to 0	−0.0476	−0.0417	−0.0214	−0.0260
Year −1 to 1	−0.0581	−0.0413	−0.0234	−0.0155
Year −1 to 2	−0.0386	−0.0334	−0.0249	−0.0180
Year −1 to 3	−0.0326	0.0063	−0.0230	−0.0198
Year −1 to 4	−0.0065	−0.0091	−0.0169	−0.0144
Panel B. Matching firm changes in operating performance matched based on industry, size, and ROA				
Year −1 to 0	−0.0208	−0.0024	−0.0122	−0.0049
Year −1 to 1	−0.0111	−0.0111	−0.0131	−0.0056
Year −1 to 2	−0.0023	0.0084	−0.0091	0.0020
Year −1 to 3	−0.0051	0.0123	−0.0110	0.0015
Year −1 to 4	−0.0017	0.0215	−0.0035	0.0070
Panel C. Wilcoxon test of significance of difference, fraud firms − matching firms				
Year −1 to 0	3.14***	3.02***	2.03**	2.00**
	(0.00)	(0.00)	(0.04)	(0.05)
Year −1 to 1	2.34**	1.92*	0.84	1.41
	(0.02)	(0.05)	(0.40)	(0.16)
Year −1 to 2	2.07**	2.49**	0.59	2.01**
	(0.04)	(0.01)	(0.55)	(0.04)
Year −1 to 3	1.02	0.85	0.55	1.10
	(0.31)	(0.40)	(0.58)	(0.27)
Year −1 to 4	0.54	2.14**	0.03	0.65
	(0.59)	(0.03)	(0.98)	(0.52)

3.5.2. Multivariate regressions of the changes in operating performance of the fraud firms

We now examine the changes in the ROA of the fraud firms from year (−1) to year (+1) in a multivariate regression setting, utilizing the same explanatory variables that have the power to explain the changes in the relationship with the fraud firm's customers. In Table 8, models (1)–(4), we begin by examining the measures of fraud severity, specifically, if the case is dismissed, if the case involves financial misrepresentation, the dollar amount of compensation requested, and the dollar amount of the settlement. We find that firms with more severe frauds tend to have a more negative change in ROA after the fraud. In particular, we find that firms accused of financial misrepresentation (model (2)) and suits with a larger resolution amount (model (4)) have a significantly negative relationship with the size of decline in the ROA. As reported in prior studies, financial misrepresentation related to information disclosure often results in the largest legal damages (Ferris et al., 2007). Therefore, results in models (2) and (4) suggest that the more severe is the fraud, the greater will be the decline in the firm operating performance. On examining the industry characteristics, we find that the industries with a greater percentage of firms with large customers have a significantly larger decline in ROA (model (6)). Finally, firms with less information asymmetry (as measured by the presence of analyst coverage) have a less negative decline in ROA (model (8)). These results are consistent with our conjecture that frauds can in fact result in a decline in performance due to customer sanctions on the fraud firm.

In Table 8 model (9), we examine the relationship between the decline in ROA and the bargaining power of the fraud firm over its large customer. We find that the weaker the bargaining power of the fraud firm over its large customer, the greater is the decline in its operating performance around the fraud event. This result implies that a fraud firm with weaker bargaining power may be subjected to more strict reputational sanctions by the customer.

However, if the decline in the operating performance of the fraud firms is caused by their large customers, this leads to a logical question: What is the transmission mechanism whereby customer reputational sanctions lead to a decline in the fraud firm's operating performance? Our hypotheses suggest that the fraud firms will have a substantial increase in the SG&A/assets ratio (selling, general, and administrative expenses over total assets) after the detection of fraud, largely because of the deteriorating relationships with their customers. We, therefore, examine the change in SG&A/assets ratio of the fraud and matching firms after the detection of fraud. We find in the Internet Appendix Table A.2 that there is a substantial increase in SG&A/assets for fraud firms, consistent with this conjecture. When we repeat our regression analyses with the change in ROA as the dependent variable and the change in SG&A/assets ratio as the independent variable, we find a negative and statistically significant coefficient on the change in SG&A/assets (Table 8 model (10)). This implies that at least part of the decline in the fraud

Table 8
Regression results for change in fraud firm's ROA from year −1 to year +1 around the fraud event.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. The dependent variables are the change in the firm's ROA (Panel A) and the change in the firm's selling, general, and administrative (SG&A)/total assets (Panel B) from the year before the fraud year to the year after the fraud year. Standard errors clustered by industry are reported below the coefficients. All regressions include control variables of log(1 + firm age), the relationship history, the fraud firm market capitalization, Tobin's Q, fraud firm leverage, and an indicator variable taking a value of one if the fraud firm and its customer are in the same industry and zero otherwise. *, **, and *** signify significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	2SLS
Size of legal sanctions												
Dismissed case (indicator)	−0.065											
	(0.113)											
Financial misrepresentation (indicator)		−0.164***										
		(0.051)										
Compensation requested ($ millions)			−0.007									
			(0.010)									
Resolution amount ($ millions)				−0.001*								
				(0.001)								
Industry characteristics												
High competition industry (indicator)					0.050							
					(0.140)							
Percent of firms serving large customers						−6.033**						
						(2.538)						
Information asymmetry												
Stock return volatility							−0.160					
							(0.259)					
Analyst coverage (indicator)								0.219**				
								(0.076)				
Bargaining power												
Percent of fraud firm sales to customer									−0.522*			
									(0.290)			
Change in cost of doing business												
Change in SGA/assets										−0.453***		
										(0.102)		
Endogeneous variables												
Fraud firm (indicator)											−0.184***	
											(0.062)	
Fraud firm (instrumented variable)												−0.163*
												(0.096)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168	168	98	57	168	168	168	168	168	168	336	336
Pseudo-R^2	27.27	28.80	41.49	45.03	26.97	30.83	27.05	29.79	29.31	32.80	16.31	20.91

firm's operating performance can be attributed to the increase in the costs associated with finding new customers after the detection of a fraud.

3.5.3. Changes in the operating performance of the fraud firm controlling for strategic fraud

One of the issues of our results reported in Tables 7 and 8 is that although our sample of fraud firms shows a significant decline in the operating performance relative to the non-fraud firms, this decline could be the result of a strategic fraud by the managers in response to the anticipation of these declines in performance (Maksimovic and Titman, 1991). In this case, the decline in the operating performance in itself is the *cause* of fraud. Alternatively, there may be an omitted variable that explains both, the commission of fraud and the decline in operating performance. To rule out these possibilities, we employ an instrumental variables approach (2SLS). We first report an OLS regression in Table 8 model (11) showing that the fraud firms have a significantly higher decline in operating performance after the fraud compared to the matching firms. However, if there are omitted variables or if the operating performance is in itself a cause of the fraud, then our OLS regression does not generate consistent estimates of the coefficients. In this case, our motivation for using an instrumental variables approach is to show that the fraud actually *causes* the decline in ROA that we observe for the fraud firms.

To be consistent with our earlier empirical results, we utilize our geographical instrumental variable from Tables 5 and 6. Specifically, firms that are in proximity of fraud firms are more likely to commit a fraud since firms tend to imitate the behavior of firms they are around (Glaeser et al., 1996). Utilizing this geographical instrument, we find in the first stage regression that there is a strong positively and statistically significant relationship between the percent of firms in the state that commit fraud and the likelihood of the firm to commit a fraud (not tabulated). This result is consistent with Kedia and Rajgopal (2011), who state that there is a geographic effect in terms of corporate misconduct. In our second stage regression (Table 8 model (12)), we repeat our analyses of the change in operating performance and find that even after controlling for endogeneity, there is still a negative and statistically significant relationship between fraud and the decline in operating performance. The fact that the size of coefficient on the instrumented fraud indicator (−0.16) is almost identical to the OLS estimate (−0.18) is suggestive of the idea that most of the decline in operating performance is caused by the fraud itself.

Additionally, to confirm the usefulness of the percent of firms in the home state in the class action database in the year of the fraud as an applicable instrument, we run a Kleibergen–Papp test and find the F-statistic to be 30.52, well above the Stock and Yogo (2005) instrumental variable 10% limit of 16.38. This result implies that our instrument does not suffer from a weak instruments problem. In addition, we consider the impact of using a conditional logit regression in the first stage as utilized by Johnson et al. (2008). We find that our results are not significantly impacted by the utilization of a conditional logit model.

3.5.4. Tests to determine customer reputational sanctions as the cause for the decline in operating performance

Our results thus far show a strong relationship between the magnitude of customer reputational sanctions and the decline in the fraud firm's operating performance. However, the decline in the relationship need not cause all or, indeed, any of the decline in the operating performance of the fraud firm. To support the argument that the decline in relationship, at least in part, results in the decline of the operating performance of the fraud firm, we utilize an instrumental variables approach. In this case, our motivation for using an instrumental variables approach is to show that as the relationship performance declines, the change in percentage of sales to the large customer actually causes the observed decline in the ROA of the fraud firms.

We must first find an instrument that correlates with the decline in the relationship between the fraud firm and the customer, but not with the residuals from the explanatory equation. Since a major motivation of takeovers is to consolidate purchasing (Fee and Thomas, 2004), we utilize the fact that some of the large customers in our sample are acquired during our sample period as an instrument to evaluate the decline in relationship.[31] Specifically, we code the acquisition of any large customer within one year of the fraud as a takeover. For instance, Compaq was a large public customer for the Netro Corporation, a firm that committed fraud in 2001. Compaq was also acquired by Hewlett Packard in 2001, a fact that may have led to the decline in the relationship between Compaq and Netro Corporation, which is unrelated to the performance of Netro Corporation, controlling for industry characteristics around that time.

We find that N = 38 (22.6%) customer firms or relevant divisions in our sample are acquired within a year of the fraud. We code these firms as being acquired and utilize this indicator as an instrumental variable in our 2SLS regressions. In Table 9 model (1), we utilize this instrument as well as log(1 + firm age) and the relationship history as instruments for the first stage regression, with the future relationship length as the dependent variable. The second stage regression in Table 9 model (2) shows that even after controlling for the endogeneity in the regressions, the instrumented change in the relationship length is significantly related to the decline in the fraud firm's operating performance (ROA). This result is consistent with the hypothesis that at least part of the decline in the operating performance of the fraud firm is caused by the decline in the relationship with the large public customer.

In Table 9 models (3) and (4), we repeat our analyses using the change in the percent of sales as the measure for the decline in the relationship. We find in model (3) that being acquired is significantly related to the decline in the relationship of the customers with the fraud firms as measured by the change in the percent of firm sales to the customer.[32] Model (4) shows that the change in ROA of the fraud firms is significantly related to the instrumented change in the percent of firm's sales. Once again, these results support the causal relationship between the decline in relationship and the operating performance of the fraud firm.

We then examine our 2SLS regressions to ensure that our results are not driven by econometric issues such as a weak instruments problem. The results reported in Table 9 show a 2SLS regression setup with standard errors clustered by industry. As such, we get a weak identification (Kleibergen–Paap Wald statistic = 7.67). However, this value is marginally larger than the Stock and Yogo (2005) critical values, but Wald-type statistics can deviate arbitrarily from their normal levels under certain conditions (Cruz and Moreira, 2005).

[31] We also code the acquisition of a division that has a relationship with the fraud firm as “acquired,” even though the whole customer firm is not acquired. This is the case with N = 16 of the customer firms coded as acquired.

[32] We do not include log (1+ firm age) and relationship history as instruments in model 3 for the sake of consistency, but we find that our results are qualitatively similar even if we do include them.

Table 9
Regression results of change in ROA from year −1 to year +1 around the fraud event controlling for endogeneity of relationship decline.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. The dependent variable is the change in the firm's ROA from the year before the fraud year to the year after the fraud year. Standard errors clustered by industry are reported below the coefficients. All regressions include control variables of log(1 + firm age), the relationship history, the fraud firm market capitalization, Tobin's Q, fraud firm leverage, and an indicator variable taking a value of one if the fraud firm and its customer are in the same industry and zero otherwise. *, **, and *** signify significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Stage 1	Stage 2	Stage 1	Stage 4
	Dependent variable = future relationship duration	Dependent variable = change in ROA	Dependent variable = change in percent sales	Dependent variable = change in ROA
Instrumental variables				
Customer taken over (indicator)	−1.084***		−0.129*	
	(0.387)		(0.061)	
Log(1 + firm age)	0.722**			
	(0.327)			
Relationship history (years)	−0.049			
	(0.076)			
Customer reputational sanction measures				
Instrumented future relationship length (years)		0.198**		
		(0.076)		
Instrumented change in percent of sales				1.916*
				(0.985)
Control variables	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes
N	168	168	114	114
Pseudo-R^2/R^2	44.61	8.65	30.76	7.39

3.6. Fraud firm and customer wealth effects

The prior literature has focused almost entirely on the wealth effects of fraud, trying to determine the costs of firms committing fraud (Karpoff et al., 2008b). As such, our analyses would not be complete without considering these event study-based measures from prior studies. We begin in Table 10 Panel A by examining the class action filing date's cumulative

Table 10
Fraud firm's abnormal returns on class action filing and trigger date.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. *, **, and *** signify that differences measured by *t*-test and Mann–Whitney test are significant at the 10% and 5% levels, respectively.

	Mean	Median
Panel A. Class action lawsuit and trigger date abnormal returns and wealth effect for fraud firms		
Class action file date		
N = 168		
CAR(−1, 1)	−4.63%***	−1.95%
t-Statistic/*z*-statistic	4.35***	3.87***
Trigger date		
N = 109		
CAR(−1, 1)	−23.87%	−22.04%
t-Statistic/*z*-statistic	12.32***	8.35***
Panel B. Class action lawsuit and trigger date abnormal returns and wealth effect for large public customers of fraud firms		
Class action file date		
N = 168		
CAR(−1, 1)	−0.74%	−0.26%
t-Statistic/*z*-statistic	2.99**	2.54**
Trigger date		
N = 97		
CAR(−1, 1)	−0.84%	−0.23%
t-Statistic/*z*-statistic	1.79*	1.17

abnormal return from day −1 to day +1, where day 0 is the filing date and/or the trigger date for the class action lawsuit. To calculate our CAR(−1, 1), we run a market model regression using the equally weighted index. We find that the mean class action file date CAR(−1, 1) is significant at −4.63%, and the median CAR(−1, 1) is significant at −1.95%. These values are substantially smaller in scale than many of the prior studies utilizing SEC investigations (Karpoff et al., 2008b), since class action suits can be of a more frivolous nature than the SEC actions used in the prior studies. Most importantly, however, for a subset of firms where we can determine the trigger date, we find that the CAR(−1, 1) is significantly larger in scale at −23.87%, consistent with the prior studies.

In Table 10 Panel B, we report the novel findings that large customers of the fraud firms also have a significantly negative mean CAR(−1, 1) of −0.74%. Likewise, on the trigger date, the customers suffer with a slightly larger significantly negative CAR(−1, 1) of −0.84%. Overall, these results suggest that fraud has a significant impact not only on the fraud firm itself, but also on the large customers of the fraud firm, as the impact moves down over the supply chain.

We now examine the CAR(−1, 1) of the fraud firms in a multivariate OLS setting. In Table 11, we begin by examining the impact of the legal sanction on the CAR(−1, 1). We find from model (1) that when the case is dismissed, the CAR(−1, 1) has a 3.12% more positive announcement day return. However, the presence of both a fraudulent disclosure and a larger resolution

Table 11
Fraud firm's CAR(−1, 1) regression results.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. The dependent variable is the market model cumulative abnormal return (CAR(−1, 1)) from filing day −1 to filing day +1 for firms with a class action lawsuit. The market model cumulative abnormal return is calculated using the equally-weighted index and betas are calculated using data from day −255 to day −46 prior to the class action filing date. Standard errors clustered by industry are reported below the coefficients. All regressions include control variables of log(1 + firm age), the relationship history, the fraud firm market capitalization, Tobin's Q, fraud firm leverage, and an indicator variable taking a value of one if the fraud firm and its customer are in the same industry and zero otherwise. *, **, and *** signify significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Size of legal sanctions												
Dismissed case (indicator)	3.118* (1.693)											
Financial misrepresentation (indicator)		−4.636** (2.130)										
Compensation requested ($ millions)			0.022 (0.152)									
Resolution amount ($ millions)				−0.047* (0.023)								
Industry characteristics												
High competition industry (indicator)					−13.274* (7.872)							
Percent of firms serving large customers						−111.649** (50.230)						
Information asymmetry												
Stock return volatility							−14.048** (5.188)					
Analyst coverage (indicator)								5.679* (3.368)				
Bargaining power												
Percent of fraud firm sales to customer									−4.270*** (1.348)			
Customer sanction measures												
Change in percent of sales										6.684* (3.691)		
Future relationship length (years)											−0.527 (0.462)	
Change in ROA												3.291* (1.822)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168	168	98	57	168	168	168	168	168	114	168	168
Pseudo-R^2	52.87	53.90	63.96	68.50	51.98	53.73	52.74	57.49	52.18	67.14	52.36	53.02

Table 12
Large customer's CAR(−1, 1) regression results.
For each firm in the Stanford Law School Securities Class Action Clearinghouse database from 1996 to 2009, we review the COMPUSTAT segment level files to determine if the firm discloses a large public customer in the year of the class action filing. We then use the universe of firms in COMPUSTAT to classify customers as public or non-public. This yields N = 168 firms in the database with a large public customer. The dependent variable is the market model cumulative abnormal return (CAR(−1, 1)) from filing day −1 to filing day +1 for the large customers of firms having a class action lawsuit. The market model cumulative abnormal return is calculated using the equally-weighted index and betas are calculated using data from day −255 to day −46 prior to the class action filing date. Standard errors clustered by industry are reported below the coefficients. All regressions include control variables of log(1 + firm age), the relationship history, the fraud firm market capitalization, Tobin's Q, fraud firm leverage, and an indicator variable taking a value of one if the fraud firm and its customer are in the same industry and zero otherwise. *, **, and *** signify significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Size of legal sanctions														
Dismissed case (indicator)	0.586													
	(0.858)													
Financial misrepresentation (indicator)		−1.443*												
		(0.752)												
Compensation requested ($ millions)			0.016											
			(0.038)											
Resolution amount ($ millions)				−0.014***										
				(0.002)										
Industry characteristics														
High competition industry (indicator)					−4.219***									
					(0.665)									
Percent of firms serving large customers						8.975*								
						(14.614)								
Information asymmetry														
Stock return volatility							−0.797							
							(2.162)							
Analyst coverage (indicator)								0.963**						
								(0.435)						
Bargaining power														
Percent of fraud firm sales to customer									1.656*					
									(0.846)					
Percent of customer's cost of goods sold attributable to fraud firm										−2.153**				
										(1.024)				
Customer reputational sanction measures														
Fraud firm abnormal returns											0.049**			
											(0.002)			
Change in percent of sales												−2.735		
												(1.917)		
Future relationship length (years)													−0.039	
													(0.210)	
Change in ROA														0.726**
														(0.279)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168	168	98	57	168	168	168	168	168	168	168	114	168	168
Pseudo-R^2	27.93	31.96	40.68	53.13	27.34	27.55	27.39	28.71	27.95	27.68	29.91	45.48	27.38	28.32

amount results in a significantly more negative announcement day return for the fraud firm (models (2) and (4), respectively). When we examine our measures of industry characteristics and information asymmetry, we find that high industry competition (model (5)), a greater percentage of firms with large customers (model (6)), and higher stock return volatility (model (7)), all result in a more negative CAR(−1, 1). In addition, we find that the presence of analyst coverage (model (8)) tends to ameliorate the bad news of the fraud, since these firms have a significantly less negative CAR(−1, 1). When we examine the relationship between the CAR(−1, 1) and our measure of the fraud firm's bargaining power, firms with a weaker bargaining power over their large customers have significantly more negative announcement day returns (model (9)). This result is consistent with Table 8 model (9), where firms that have a weaker bargaining power with their large customers suffer more decline in ROA.

On examining the customer reputational sanction measures, we find results that are consistent with our prior tables. For instance, when we examine proxies for the sanctions by large customers, we find that the larger the decline in percent of sales (model (10)) and the change in ROA (model (12)), the larger is the decline in the stock price. These results imply that reputational losses estimated by the event study approach actually reflect the lost sales and increased selling costs related to the firm's business relationship with large customers, namely, the customer reputational sanctions.

We now run qualitatively similar regressions using the large customer's CAR(−1, 1) as the dependent variable with similar explanatory variables as in Table 12. Due to the size of the fraud firm's customers, we find substantially weaker results compared to our previous regressions using the fraud firm's own CAR(−1, 1). However, we still find that when a firm is accused of fraudulent disclosure, the customer CAR(−1, 1) is significantly lower by 1.44% (model (2)). We also find that when the resolution amount is larger, the customer CAR(−1, 1) is significantly more negative (model (4)).

Using our measures for industry characteristics and information asymmetry to explain the customer announcement day returns is qualitatively similar to the prior results. Firms with high industry competition (model (5)) have significantly more negative customer CAR(−1, 1), but firms with lower information asymmetry, as measured by analyst coverage (model (8)), have a less negative customer CAR(−1, 1).

Moving on to the measures of the fraud firm's bargaining power, we find that when the fraud firm's bargaining power is weaker, the customer CAR(−1, 1) is more positive (model (9)). This may be because customers are able to extract more concessions from the fraud firm ex post if the percentage of sales of fraud firm is higher. In contrast, model (10) shows that when the customer's bargaining power over its fraud supplier is weaker, as measured by the percent of customer cost of goods sold, the customer CAR(−1, 1) is more negative. Other measures for relationship value show results similar to the prior tables. When the relationship is more important, the customer CAR(−1, 1) tends to be more negative.

We also examine the relationship between the customer's CAR(−1, 1) and the fraud firm's CAR(−1, 1). This regression (model (11)) is particularly important, because if the same economic source is causing the decline in the values of fraud and customer firms, then these values should be significantly related. Further, this regression allows us to calculate the economic importance of customer sanctions on the fraud firm. Our results show a positive and statistically significant relationship between the fraud firm and customer CAR(−1,1), implying a single source for both sets of economic losses associated with the fraud. In addition, the magnitude of the relationship suggests that a 1% decline in the fraud firm's stock performance is associated with a 0.05% decline in the customer's stock performance. While this may seem economically small, it is actually quite large due to the significant difference in the sizes of the fraud firm and the customers. In dollar amounts, the implication is that a loss of $1 in the value of the large customer is associated with a loss of $1.15 by the fraud firms. In addition, we find that firms with a larger decline in ROA exhibit a significantly larger decline in customer CAR(−1, 1) (model (14)). Therefore, when we estimate the total social costs of fraud, we have to consider the spillover effect of damaged reputation. Our direct approach allows us to quantify the size of this spillover effect.

One important issue raised by Karpoff et al. (2012) is that the announcement day (or class action filing day) cumulative abnormal return (CAR) is not a good proxy for the total wealth effects of fraud. Problems like pre-announcement information leakage as well as difficulty in determining the precise date of fraud undermine the reliability of this measure. We find that for our sample of firms with class action filings against them, this effect is less of a concern. First, only a minority of these firms (9%) are charged with other actions, such as, SEC and/or Department of Justice actions. Second, we are able to get a perfect measure of the class action filing date from the Stanford Class Action Database. Finally, as we focus this study mostly on our direct measures, the majority of our results are not significantly impacted by the shortcomings of the event study methodology.

To allay the concerns regarding the use of our methods, in untabulated tests, we repeat our analyses in Tables 11 and 12 for the N = 109 fraud firms with an exact trigger date discernible in the data and the N = 97 large customers of these firms with sufficient return data. We find that our results are qualitatively similar, although, somewhat statistically weaker due to the reduced sample size. Further, we find that none of our legal sanction measures is significant, likely due to the fact that the firms with a specific trigger are all associated with more severe frauds and the firms without a trigger tend to be dismissed.[33]

Overall, our results strongly support the idea that customers impose strict sanctions on their suppliers who commit fraud. Our results also support the idea that fraud has a significant impact on the customer firms as well.

[33] In addition, we examine the CAR(−1,1) for the fraud firms and their large customers around the class action lawsuit resolution. We find that the fraud firms have a positive but insignificant CAR(−1, 1) of 0.12% (t-stat = 0.15) implying that the market correctly interprets the impact of the fraud resolution on average. Likewise, the insignificant customer CAR(−1, 1) of 0.47% (t-stat = 1.22) upon resolution of the lawsuit implies that the market correctly imputes the information disclosed at the resolution of the lawsuit.

4. Additional tests and robustness checks

4.1. Comparison of financial penalties with customer reputational sanctions

Previous studies, including Karpoff et al. (2008b), report that the destroyed wealth of the fraud firm upon detection of fraud far exceeds the financial penalties imposed on the firm by the SEC. We examine this issue with our three direct measures of customer reputational sanctions. We compare the size of direct penalties imposed by the government sanctions (SEC and DOJ) with the size of sanctions imposed by large customers. Specifically, we calculate the cost burden on the fraud firm as a result of its deteriorating trading relationship with its customers and increased selling costs.[34] In picking these particular categories, we have tried to focus on costs directly attributable to government sanctions or customer sanctions.[35] Some variables, such as net income, could decrease because of lost sales to the large customer, or an increase in SG&A, making this variable difficult to interpret. In the first two columns of Internet Appendix Table A.3, we report the mean and median direct costs for these variables. Note that if there is no cost associated with a particular firm for these variables, we replace that cost with a zero.

We find that the direct costs associated with government fines have a mean (median) value of \$1.89 (\$0.00) million. Likewise, the mean (median) costs of class action fines is \$11.72 (\$0.00) million.[36] We also find that the mean (median) loss of sales to the large customer account for \$21 million (\$0.0 million) in our sample period. In addition, we find that the fraud firms exhibit a mean (median) increase of \$21 million (\$2 million) in SG&A expenses.

One difficulty of this methodology is converting these direct costs into a loss in wealth. We follow the methodology of Karpoff et al. (2008b) by using industry medians to calculate the impact of the lost sales, and increased SG&A on the fraud firm. To calculate the Lost Sales Effect, we multiply the cost of lost sales by the industry median market-to-sales ratio for the fraud firm's industry. To calculate the increased SG&A effect, we multiply the increased SG&A by the industry median market-to-SG&A for the fraud firm's industry.[37]

Consistent with the prior literature, we find that the direct costs from Government Fines and Class Action Fines are small compared to the wealth effects from the lost sales and increased SG&A effect. We find that the wealth effect from lost sales has a mean (median) of \$104 million (\$0.0 million). In addition, the increased SG&A Effect has an even larger wealth impact with a mean (median) value of \$138 million (\$8.25 million). These results imply that the direct fines are quite small, but the product market costs are substantially larger.[38]

Our results support the idea that customer reputational sanctions are a real cost for fraud firms. These costs are much larger than the sanctions imposed by the government through fines and penalties or through the courts through class actions against the fraud firms as suggested in the previous studies, including Karpoff et al. (2008b).

4.2. Effects of adverse information

Although our instrumental variables approach should help to rule out any interpretations other than customer reputational sanctions for our operating performance decline results, we now conduct a battery of tests to rule out any possible alternative explanations. One of the alternative explanations for our results is that the decline in the future operating performance is not due to reputational sanctions from the fraud firm's customers, but rather due to the adverse information disclosed by the fraud itself. For instance, "the announcement of a fraud may…reveal managers' unfavorable information about the firm's prospects" (Karpoff and Lott, 1993). To rule out such adverse information effects, we utilize many of the same tests conducted by Karpoff and Lott (1993).

If fraud firms have some deficiency in their operations or management quality, then we might expect the market to partially anticipate this before the fraud. However, we uncover no evidence that investors or analysts are able to anticipate bad news about the fraud prior to the actual fraud disclosure. For instance, for the $N = 153$ fraud firms with sufficient stock return data to calculate returns 230 days prior to the fraud disclosure, we find a *positive*, but insignificant CAR$(-230, -2)$ of 0.05% ($z(-230, -2) = 0.50$) leading up to the class action filing. These results suggest that rather than anticipating the fraud events, the stock market is seemingly surprised by the event, which is inconsistent with the notion that information effects may explain the stock price reactions to the fraud announcements.

We also examine the time-trend related to analyst earnings forecasts around the time of the fraud. If analysts are able to accurately forecast the decline in the earnings associated with the fraud, then this would imply that our results may be caused by an information effect. We utilize the IBES analyst forecast data for the eight quarters leading up to the fraud event. We focus on

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[34] In addition, we calculate the size of the readjustment effect, but find it to be small relative to the size of the customer sanction. For a detailed discussion of the readjustment effect, see Karpoff et al. (2008b).

[35] An additional limitation of our methodology is that we cannot be sure that our direct costs are caused only by the changes in the relationship with the large customer. For instance, SG&A may increase not only because of the decline in the relationship with the large customer, but also because the alternative large customers may, among other things, require more frequent interactions with the supplier.

[36] Note that this figure is substantially below the figure reported in Table 1, since missing resolution amounts are now replaced with zero for the settlement amount.

[37] Following Karpoff et al. (2008b), we do not make an adjustment to the Government Fines and Class Action Fines — they are presumed to translate dollar-for-dollar into a decline in the firm value.

[38] We also conduct an event study and find that the total cost of the fraud measured in an event study is \$262 million, only about 50% larger than the customer sanctions we estimate.

firms that have at least six consecutive quarters of earnings forecasts leading up to the fraud date. For the N = 39 firms with sufficient earnings data (having N = 323 firm-quarter observations), we find an insignificant positive trend in the median four-quarter-in-advance forecast earnings leading up to the fraud; the coefficient on the time trend is 0.01 (t-statistic = 0.24). These results suggest that no negative information is discovered by analysts in the quarters leading up to the fraud event. These results are tabulated in the Internet Appendix Table A.4.

4.3. Industry shocks

We are also concerned that our results may be caused by an industry shock that impacts both, the fraud firm and its large customer, thus generating our overall results. Although our instrumental variable result should rule this out, we run additional tests to confirm that our results are not caused by an industry shock. We first examine the matching firm's abnormal stock returns around the class action filing date. We utilize a fairly large event window, consistent with Karpoff and Lott (1993), to examine the long-term stock performance for the matching firms around the fraud event. If frauds are the result of an industry shock, then it is likely that the matching firms will have abnormal stock returns around the fraud event as well. We find that the CAR(+2, +30) for the matching firms is an insignificant 5.08% (z-statistic = 1.44), and the CAR(+2, +230) is an insignificant 8.62% (z-statistic = 0.19). These results imply that there is no significant industry effect around fraud events.

4.4. Readjustment effect

Subsequent to a fraud, the firm that discloses inappropriate or misleading information is likely to revise its accounting statements by modifying three aspects of its income statements: special items, accounting charges, and charge offs. Karpoff et al. (2008b) find that between 8% and 25% of the fraud firm's abnormal returns are the result of a readjustment effect due to changes in these three accounting items. This raises the question about the extent of the effect of similar accounting changes by the firms after the fraud on our results. Consistent with Karpoff et al. (2008b), we focus on special items, accounting charges, and charge offs (COMPUSTAT items spi, acchg, and nco, respectively). In our sample of N = 168 fraud firms, we find that accounting changes are always zero and net charge offs are always missing. This leads us to focus on special items in the year of the fraud and four subsequent years after the fraud. Our Internet Appendix Table A.5 compares the special items/total assets for the fraud year and four subsequent years of the fraud firms with that of the matching firms. We find that special items value for the fraud firms is significantly more negative compared to that of matching firms for the three years after the fraud. This result is not surprising since it may take some time to adjust the firm's accounting statements subsequent to the fraud and as this occurs, the fraud firms will continue to adjust their accounting statements.

It is important to note that our documented results could be strengthened by the readjustment effect. As such, we wish to rule out the idea that the readjustment effect may explain the overall findings of our study. We repeat our analyses to determine if the inclusion of special items/assets in our regressions results in a significant change in our overall regression results. For the results discussed below, we utilize the special items/assets in the year after the fraud, although our results are qualitatively similar even when we consider different time periods for calculating these accounting changes. When we include special items in the Hazard model regression (Table 4) as a control variable, we find that special items is significantly related to the hazard rate, implying that a more negative future adjustment to the special items does in fact lead to a shorter future relationship with the large customers. When we repeat Table 4, models (1)–(10), we find that all models remain statistically significant even after controlling for special items, except for models (1) and (2). However, these models specifically deal with the legal sanctions and it is likely that the legal sanctions will be significantly related to the special items measure.

On repeating our analyses of the changes in the percent of firm sales to the large customer, we find similar results using the special items measure. For instance, we find that larger (more negative) special item/assets measures are associated with significantly larger decline in the percent of sales to the large customers. However, when we repeat the analyses by examining the change in the percent of sales in Table 5 while controlling for the special items measure, we find that our results are largely unchanged. The only substantial changes are in models (1) and (2), where dismissed cases and financial information misrepresentation cases are no longer significantly related to the change in the percentage of firm sales. As previously mentioned, this is likely caused by the fact that the special items measure is significantly correlated with these measures for legal sanctions.

Moving on to the changes in the fraud firm's operating performance (ROA), we find that the changes in special items is significantly related to the change in the fraud firm's ROA, which indicates that larger write-offs are associated with larger declines in the ROA of the fraud firm. On repeating our analyses in Table 8, we find that models (2), (4), (9), and (10), all go from having significant explanatory power for the key variables to insignificant coefficients once we include the special items measure. This result is likely driven by the fact that special items measure is likely to be a good proxy for fraud size.

Finally, when we examine the relationship between the fraud firm's announcement day return and the special items, we find a negative and significant coefficient, implying that the firms with a greater (more negative) future adjustment in special items will have a less negative announcement day return. We find that on adding the special items measure as a control variable in Table 11, regressions only change the significance of models (1) and (5). However, it is likely that this impact is due to the fact that the special items measure is a proxy for fraud severity. We find that the fraud firm's special items measure is not significantly related to the customer announcement day return and thus, addition of this variable does not appreciably impact our results in Table 12 regressions.

Overall, it appears that our results are largely unchanged, even with the inclusion of special items in the years subsequent to the fraud as controls to our major results. We suggest that this measure likely correlates to the overall firm's fraud severity, thus, resulting in some multicollinearity with our other variables of interest.

4.5. Deep pockets argument

An alternative explanation to our major results is that customers of firms sued for fraud have a negative wealth effect, because they too are under close scrutiny by the plaintiffs in the cases against the fraud firms. If customers have greater resources than the fraud firms and if customers should have been able to detect inappropriate action by the fraud firms, then these large customers may also be subjected to a secondary lawsuit. We refer to this as a deep pockets argument, since customers are typically much larger than their suppliers and, thus, are more likely to have resources that make them more likely to settle a lawsuit for greater amounts than that of the fraud firms.

To rule out the possibility that the deep pockets argument explains our results, we run a battery of tests. We first examine the customer abnormal return, including customer size as a determinant. The deep pockets argument implies that larger customers should have a more negative response to such a lawsuit threat, since these firms are more likely to be sued. Inconsistent with the deep pockets argument, we find no significant relationship between fraud firms' $CAR(-1, 1)$ and the customer size. Likewise, when we separate our firms into terciles or quartiles by size, we do not find a significant relationship between customer size and fraud firms' $CAR(-1, 1)$. We then examine the customers of fraud firms to determine if these customers are ever subjected to a lawsuit subsequent to the initial suit. While we find that 32 of the customers are sued subsequent to the original lawsuit, in none of these suits is the original supplier firm ever named as a relevant factor. This result implies that there is no relationship between the original lawsuit and the customer lawsuit. Based on these results, it seems unlikely that the deep pockets argument is a substantial driver in our overall results.

5. Summary and conclusions

In this paper, we examine several testable implications of customer reputational sanctions for corporate financial misconduct. Using direct measures of customer reputational sanctions and the detailed transaction data about individual customer and supplier business dealings, we find that customer reputational sanctions do exist. Further, we establish a causal relationship between financial misconduct and the decline in the operating performance of a firm that has committed fraud. In addition, we find that the decline of the firm's operating performance as an effect of the firm's financial misconduct is the result of customer reputational sanctions, as measured by our three direct measures, through an increase in the selling costs following the detection of firm's financial misconduct. These results are all consistent with the previous studies, which suggest that a customer imposes reputational sanctions by reducing demand for the fraud firm's products.

We also find that several industry and fraud firm characteristics, which influence the value of continuing with the existing business relationships between the fraud firm and the customer, are significant determinants of the customer reputational sanctions and the fraud firm's announcement day returns. Our results imply that the customers rationally choose the intensity of customer reputational sanctions based on a comparison of the benefits and costs of imposing the reputational sanctions.

We further show that reputational losses, which are estimated from the event study approach, reflect in large part the deterioration of fraud firm's business relationship with large customers, as is implicitly assumed in previous studies. Our study provides grounds for the use of event study approach in the corporate fraud literature. In additional tests, we find that it is the damaged reputation and not the adverse information revealed by the detection of fraud that causes these phenomena. Our findings suggest that, consistent with the previous studies of corporate reputation, the consequences of the allegations of financial misconduct and the firm's reputation may significantly influence corporate policies, including the policies related to purchase and investment.

Appendix A. Additional Tests

Additional tests to this article can be found online at http://dx.doi.org/10.1016/j.jcorpfin.2013.10.005.

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