The impact of fraudulent earnings manipulation on industry rivals

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ABSTRACT

Previous work on fraudulent earnings manipulation has focused on the fraud firm. This paper broadens the scope of analysis and studies how fraud impacts the rivals of the fraud firm. Using an extension of the Cournot model we first show that a rival firm may either benefit or suffer from the revelation that one of its competitors has committed fraud. On the one hand a rival firm may benefit due to the expectation that the fraud firm will be less able to compete in the product market. On the other hand the rival firm may suffer to the extent that the revelation of inflated earnings by the fraud firm results in shareholders revising downward their assessment of future rival firm or industry-wide profits. Taking the model to the data we find that, on average, rival firms suffer a loss in value upon the revelation of fraud. However, we also find that this negative effect is not uniform across all rivals. In particular, announcement returns are higher for rival firms in more concentrated industries, for rivals of larger fraud firms, and for rivals with lower valuation uncertainty. These as well as other results in the paper are consistent with the model's predictions.

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I. *Introduction*

Recent interest surrounding the revelations of corporate fraudulent earning manipulation has centered on the fraud firms themselves. Various studies have covered questions such as what led these firms to commit fraud (e.g. Johnson et al. 2005, Burns and Kedia 2006, Bergstresser and Philippon 2006, Goldman and Slezak 2006, and Povel et al. 2007), what impact did fraud have on the wealth of shareholders (e.g. Palmrose et al. 2004, Karpoff et al. 2006, and Gande and Lewis 2007), and what are the mechanisms that in practice help detect fraud (e.g. Dyck et al. 2007).

While the shareholders of a firm that commits fraud suffer the greatest financial loss, the fraud event has potential economic implications for other "related" firms. For example, the following is a quote from a March 2002 Associated Press report concerning the revelation of wrongdoing at Global Crossing Corporation:

"*Global Crossing's sudden implosion has done more than sting shareholders, creditors and employees. It's burdened the suffering telecom industry with new worries about solvency and accounting irregularities while prompting some investors to flee the sector. 'Global Crossing was a wake-up call for a lot of people that didn't realize how bad the telecom sector had become,' ....*"

Thus, the fraudulent earnings manipulation committed by one firm can have an effect on the shareholders of rival firms.[1] In light of the above, the main goal of this paper is to shed light on the broader implications of fraud by exploring what is the impact of the revelation of fraud by one firm on the value of its industry rivals.

[1] It is also possible that fraud can have an effect on firms along the supply chain. While we do not study these firms Hertzel et al. (2007) looks at the impact of bankruptcy on firms along the supply chain.

Unlike what the above quote suggests, we argue that, *a priori*, it is not obvious that the revelation of fraud in one firm is detrimental to its rivals. The reason being that the revelation of fraud can have two countervailing effects: one coming from the expected change in market competition and the other coming from the revelation of new information about rival firm and industry-wide profits. On the one hand the revelation of fraud implies that the fraud firm will be liquidated (as with Enron), at the extreme case or, at the less extreme scenario, hampered in its ability to continue to compete with its rivals (as with Xerox). This will open up opportunities for existing firms to pick up market share and increase their value. On the other hand, observing that the true earnings of the fraud firm are actually much lower than previously believed, investors may revise downward their assessment of the potential value of the industry as a whole and of rival firms. For example, the revelation that Enron fraudulently manipulated and inflated its profits has most likely resulted in a downward revision of investor's assessment of the overall profit levels that can be generated from trading energy derivatives.

The updated value of a rival firm following the announcement of fraud will then depend on the specific characteristics of the rival firm, the characteristics of the industry, and those of the fraud firm. Namely, some rivals will stand to benefit from this announcement while others will stand to lose.

To guide our empirical analysis we develop a simple model of Cournot competition with asymmetric information and show that when fraud by one firm contains no additional information about rival firm or industry-wide profits the value of all rival firms increases upon the announcement of fraud. This is due to the fact that the indicted firm is forced to shift significant resources in order to deal with the impending litigations and thus will lower its production.[2] In contrast, when we allow for the possibility of informational spillovers on rivals, we find that shareholders use the information contained in the announcement of fraud to update their assessment of the value of the rivals. In this case we show that the value of rival firms may decrease upon the announcement. This will happen whenever the information contained in the signal (fraud announcement) is sufficiently bad for the rival firm.

The model generates a rich set of cross sectional empirical implications. For example, the analysis shows that, following the announcement of the fraud, rival firms operating in more competitive industries are more likely to decline in value, but that rivals whose valuation is known with more certainty are more likely to experience an increase in value. Furthermore, the rivals of a fraud firm whose initial valuation is more uncertain will be more likely to experience an increase in value following the announcement.

We test these, as well as other, predictions using a sample of 111 allegations of accounting fraud, from 1995 to 2005. For this sample we find that, on average, the stock price of rival firms drops by 2.34% following the announcement of fraud. More directly related to our model we find several cross sectional results that are consistent with our predictions.

One way in which we can highlight the key implications of the model is to form sub-samples of rival firms based on the variables that the model predicts should lead to either a high or a low CAR. We find that for the sub-samples that have a low score (i.e., are predicted to have the most negative announcement return) returns are strongly negative while for the sub-samples with the high score (i.e., those that are predicted to have the highest returns) returns are positive. For example, for a sub-sample of 121 rival firms that display characteristics that suggest the

[2] In our model we assume that a fraud firm has to leave the market once it is indicted of fraud. However, we would get qualitatively similar results if we assume instead that fraud results in an increase in the costs of production. Production costs can go up because many of the firm's resources will now have to be applied toward dealing with the indictment.

lowest announcement return we find an average negative CAR of -11.94%, while for the sub-sample of 115 firms with characteristics suggesting the highest CAR we find an average positive return of 4.51%. The differences in CARs between each of the high and low score sub-samples is statistically as well as economically significant. This highlights our model's ability to identify the wide range of rival responses to the revelation of fraud.

Looking at each firm characteristic in a multivariate setting we first find that the price drop is larger for rival firms that are in more competitive industries (industries with a lower Herfindahl index). The intuition for this result is that in more competitive industries it is more difficult for each rival to gain a large share of the market from the fraud firm.

Second, we find that rivals benefit more when the fraud firm is larger. This again is consistent with the idea that if the fraud firm is large there is more capacity that can be picked up by the rivals. This effect is particularly strong in concentrated industries where larger fraud firms leave more customers to be redistributed among fewer firms.

Third, we find that the announcement effect is more negative for rival firms about which there is greater initial uncertainty. The intuition for this is that if the market has less information about one of the rival firms it will use any external signal (i.e., the announcement that the earnings of a competitor are lower than previously believed) much more heavily to update its assessment of the rival's value. In further support of this inference, we find that rivals that reacted more to past earning surprises of the fraud firm (measured by the earnings response coefficient of the rival firm to earnings surprises of the fraud firm) decrease more in value following the announcement. This evidence is particularly interesting as it suggests that investors had used past (fraudulent) earnings information to update the stock price of the rival.

Fourth, we find that the rival's stock price is more likely to increase following the fraud announcement whenever there is more initial uncertainty regarding the fraud firm. The intuition here is that when there is more uncertainty about the fraud firm the market incorporates any new (negative) information about that firm with much more caution (the Bayesian updating is discounted by the overall variance).

Finally, we find that when the announcement return of the fraud firm is more negative, rivals suffer more. The intuition here is that when the downward updating of the fraud firm's earnings is larger, all things being equal; it translates to worse news for all the rivals as well.

The two effects described above, termed the 'competition' effect and the 'information spillover', or 'contagion' effect, apply to many scenarios. However, these effects have not been studied in the context of fraud and more importantly there is limited work investigating their impact on the firm level.

In contrast to the related work of Xu et al. (2006) and Lang and Stulz (1992) who focus on an industry level analysis (see discussion in the following section) our paper shows the details of how fraud propagates to rivals and explains what fraud firm, rival firm, and industry characteristics influence the contagion and the competition effects. In particular, we find that our predicted firm level characteristics significantly explain cross sectional variations in announcement returns even within industries. In this sense, our paper provides a more complete picture of the overall impact that recent fraud cases have had on investors.

In addition, our analysis may give some insight as to how one can partly hedge against the risk of fraud by indicating which industry rivals stand to benefit. One can also use our results to learn more about which firms and in which industries we would expect to see more "whistle blowing" activity by competitors (e.g. Dyck et al. 2007). This may bear on the more general discussion of the possibility of efficient self-regulation (e.g., Bebchuk, 2007) as we believe that rival firms that get hurt from their competitor's fraud will be more inclined to commit ex ante to be self-regulated. Finally, regulators may use this type of analysis to guide their limited monitoring resources to identify fraudulent activity in those industries where the negative impact of fraud is likely to have more widespread consequences (e.g. focus on firms who have a bigger impact on the rest of the industry).

The rest of the paper is organized as follows: in Section II we provide a brief review of the literature, in Section III we outline the model and derive the main empirical implications which are then tested in Section IV, and Section V concludes.

II. *Literature review*

Our paper is closely related to two main strands of the literature. The first strand includes papers that examine the causes and consequences of corporate fraud. The second strand deals with the analysis of the spillover effects of events in one firm to others.

Research on corporate fraud has taken on many different perspectives. Karpoff et al. (1999) studies the consequences associated with firms that are indicted for procurement fraud when signing military contracts with the government. Burns and Kedia (2006), and Bergstresser and Philippon (2006) suggest that earnings management and financial misreporting are motivated by stock based compensation as they are positively related to higher levels of executive stock-based compensation.[3] Johnson et al. (2005) shows a positive association between the use of stock-based compensation and fraudulent manipulation of accounting statements while Erickson et al. (2006) argues that there is no such link. Finally, Dyck et al. (2007), and Yu and Yu (2007) look at different aspects relating to fraud detection.

[3] Goldman and Slezak (2006) show this in a theoretical model of optimal executive compensation.

The literature on spillover effects includes many papers each focusing on a different event. Eckbo (1983), and Eckbo and Wier (1985) look at the impact of mergers on industry rivals. Bittlingmayer and Hazlett (2000) studies whether antitrust rulings against Microsoft are good news for Microsoft's competitors. Fich and Shivdasani (2006) studies the impact of having directors on a company's board who also serve as directors on a board of another company indicted of fraud. Gande and Lewis (2007) shows that firms facing a shareholder class action lawsuit suffer a loss in value before their actual indictment as shareholders lower their valuations following earlier events in which other firms in the same industry were served with a similar suit. Finally, Tookes (2007) studies the incentive of insiders to trade on their private information in the stocks of competitor firms.

The closest papers to our own work are Lang and Stulz (1992) and Xu et al. (2006). These papers examine the impact of bankruptcy and earnings restatement, respectively, by one firm on the stock price of its rivals. Lang and Stulz (1992) investigates the impact of bankruptcy on rivals and finds that while the overall impact is to lower rival's value, in highly concentrated industries with low leverage the effect is positive. While our results on industry concentration are consistent with those of Lang and Stulz (1992), we provided a more comprehensive analysis both on the industry level and on the firm level. Furthermore, the event of fraud that we analyze is different than the bankruptcy event analyzed in their paper as most of the fraud firms in our sample do not go bankrupt in the two years following the announcement.

Xu et al. (2006), finds a negative average response by rivals to an earning restatement. The paper further shows that industry concentration is not an important factor in determining the cross sectional effect of an earnings restatement.[4] Unlike our fraud events, earning restatements

[4] In a follow-up paper to Xu et al. (2006), Durnev and Mangen (2007) find that competitor price declines are due to past inefficient investments.

are not typically followed by any lawsuits and, hence, it is not surprising that their study cannot identify any competition effects.

III. *Model*

We model an industry in which a set of $i=1..N$ firms compete in the product market. Product market competition follows the Cournot-Type model in which firms compete over quantities. Demand for the product is given by the aggregate price function $P = a - Q$ where $Q = \sum_{i=1..N} q_i$ and q_i is the quantity produced by Firm i. For simplicity, we assume that all firms have similar production functions except for Firm 1 (later this will be the fraud firm) and Firm 2 (the representative rival firm analyzed empirically). In particular, we assume that Firm 1 produces a quantity $q_1 = A_1 e_1$ at a cost of $C_1(e_1) = c_1^1 e_1 + c_1^0$, Firm 2 produces a quantity $q_2 = A_2 e_2$ at a cost of $C_2(e_2) = c_2^1 e_2 + c_2^0$, while for firms $i=3..N$ the production function is $q_j = Ae_j$ and the cost of production is $C_j(e_j) = ce_j$. For all firms, A represents the size of the assets used for production, e represents the human capital (or effort), and c (c_i^1) represents the marginal cost of investment.

The model has three periods. In the last period, $t=2$, each firm chooses its level of production and profits are realized. In the first period, $t=0$, shareholders make an assessment about firm value given their information set. This value assessment is updated at $t=1$ once investors learn about the fraud committed by Firm 1.

Note that we assume that all the model parameters are known to each of the firms. However, shareholders who value these firms in the stock market are uncertain about the true fixed costs of production. The information structure is as follows.

Assumption 1 *In the first period investors are uncertain about the values of* c_1^0 *and* c_2^0 *where* $c_1^0 = c_{12} + c_1$ *and* $c_2^0 = c_{12} + c_2$ *with the belief that* $c_{12} \sim N(\mu, \Sigma_{12})$ *and that* $c_i \sim N(0, \Sigma_{\theta_i})$. *In the second period, following the revelation of fraud by Firm 1, investors obtain a signal S, where* $S = c_{12} + c_1$. *Here,* c_1 *is an independent noise term specific to Firm 1 and* c_{12} *reflects the common cost component of firms 1 and 2.*

Uncertainty is modeled in the simplest possible manner that allows us to capture the salient features of the economic event. The uncertainty about Firm 1 has an idiosyncratic component as well as a "market wide" component. Namely, the cost of Firm 1 can be viewed as partly relating to Firm 1's specific characteristics and partly relating to a factor shared by all firms in that industry. In particular, c_{12} measures to what extent the fraud firm and the "representative" rival have correlated costs. The revelation of fraud causes investors to update on both components where the update on c_{12} affects the rival's firm value.

Given the above structure each firm, *i*, faces the following maximization problem,

$$\max_{e_i} \; \mathrm{E}[q_i P - C_i(e_i)] \tag{1}$$

The first order condition for Firms *i*=1 and 2 yields,

$$e_i = \frac{1}{A_i}(P - K_i). \tag{2}$$

and the first order condition for Firm $j \neq 1,2$ yields,

$$e_j = \frac{1}{A}(P - K), \tag{3}$$

where $K_i \equiv \frac{c_i^1}{A_i}$ and $K \equiv \frac{c}{A}$.

III.1. *Equilibrium*

In order to calculate the value of each firm we assume that risk-neutral investors form expectations, at *t=0*, regarding the parameters of the firm's maximization problem. These expectations are then updated, at *t=1,* following the revelation that Firm 1 committed fraud. For expositional purposes we first solve for the equilibrium value of Firm 2 prior to the realization of Firm 1's fraud and then solve for the updated value following the revelation of fraud.

III.1.1. *Prior to the realization of fraud*

Before fraud is realized shareholders value the firms according to their expected profits. To calculate these profits we make the following assumption that guarantees that costs are not too high so as to render negative profits (i.e., production of a negative quantity) for Firm 1.

Assumption 2 *Firm 1's size adjusted cost of effort,* K_1, *is restricted to be less than* $\frac{a+(N-2)K+K_2}{N}$.

Given this assumption it is a straightforward exercise to compute the Nash equilibrium of the competitive game. As mentioned, our focus for the empirical analysis will be on Firm 2.

Lemma 1 *In the Nash equilibrium of the game Firm 2 produces a quantity*

$$q_2^* = \frac{1}{N+1}[a + K_1 + (N-2)K - NK_2], \tag{4}$$

and makes an expected profit of,

$$\Pi_2^* = q_2^{*2} - \mu . \tag{5}$$

Proof: See Appendix

The solution represents a standard Cournot equilibrium with the exception that here the size of the firm's assets, *A*, plays an important role in determining the quantity produced. The larger the size of the assets used for production the lower the firm's unit cost of effort. Hence, the larger *A* is the more it produces and the less its competitors produce.

III.1.2. *Following realization of fraud*

At $t=1$, following the realization that Firm 1 was caught committing fraud, investors recalculate the expected profits (values) of the remaining firms. In particular, they now have to consider that Firm 1, as a result of having committed fraud, will be forced to stop all production and leave the market. While this is an extreme assumption it is reasonable to assume that having been caught committing fraud will have a significant effect on the firm's ability to continue operating and producing at the same capacity and with the same intensity as before. For simplicity, we therefore model a firm that has been indicted for committing fraud as if it were completely liquidated and forced to leave the market (this is true, for example, for Enron). As mentioned before this assumption does not change the qualitative nature of the results.

While the direct effect of fraud is to reduce competition from the fraud firm, it is also likely that fraud may have an additional effect through the fact that investors use the new information to update their assessment of the value of their own firm. For example, if investors believe (in the first period) that Firm 1's profits are going to be high due to the joint assessment that industry costs as well as Firm 1 costs are low then when information about the revelation of fraud arises in the second period investors update downward their beliefs about Firm 1's profitability. If all of the new information is viewed as specific to Firm 1 (e.g., costs of production at Firm 1 were much higher than was depicted in the accounting statements) then the revelation of fraud should have no additional impact on the other firms in the industry. If, on the other hand, some of the new information is not firm specific (e.g., profit reports where inflated due to the fact that industry costs are actually higher than previously believed) then the revelation of fraud by Firm 1 will likely have an adverse effect on the valuation of other firms in the industry. To analyze these scenarios in detail we first solve for the updated value of Firm 2 and then compare it to the value before the revelation. This comparison will then be used as a proxy to measure the "announcement effect" of the fraud. In this case we now have the following equilibrium,

Lemma 2 *Following Firm 1's fraud Firm 2 will produce a quantity of*

$$q_2^{**} = \frac{1}{N}[a + (N-2)K - (N-1)K_2]. \qquad (6)$$

Shareholder's updated valuation of Firm 2 will be,

$$\Pi_2^{**} = (q_2^{**})^2 - \{\mu + (S-\mu)\frac{\Sigma_{12}}{\Sigma_{12} + \Sigma_{\theta_1}}\} \qquad (7)$$

A comparison of Lemma 2 and Lemma 1 illustrates the impact of fraud on the remaining firms in the industry. First, each of the remaining firms will now produce a larger quantity and make more profits since there are *N-1* competing firms instead of *N* as before. Second, the value of each firm can also decrease due to the potential negative updating regarding the larger cost component.

Lemma 3 below demonstrates what happens to firm value for the rival firm when no information updating occurs.

Lemma 3 *In the absence of any information effect the profit of Firm 2 increases following the revelation of fraud.*

Proof: See Appendix

The above Lemma demonstrates that when the revelation of fraud has no informational impact on other firms in the industry then the expected profits generated by the remaining firms will always go up. Hence, we should also expect their market valuations to increase. The intuition is very simple. Less competition implies that each firm can now produce a larger quantity to pick up the slack left by the fraud firm. This results in higher profits to all. The interesting case then will be to look at the outcome of fraud when we incorporate uncertainty into the model.

III.2. *Empirical implications*

In this section, we start by investigating the determinants of the sign of the announcement effect, $\Delta\Pi = \Pi_2^{**} - \Pi_2^{*}$, once we allow for investors to use the revelation of fraud as a signal on which they can update their assessment of the viability of the rival firm. Then we derive several cross sectional implications about which firms and in which industries the effect should be more pronounced.

Lemma 4 below describes the conditions under which the revelation of fraud will result in a value loss to a rival firm.

Lemma 4 *There exists a constant value* $S_{Cutoff} = F(N, \Sigma_{12}, \Sigma_{\theta_1}, K_2, K_1)$ *such that* $\Delta\Pi \geq 0$ *if and only if* $S \leq S_{Cutoff}$. *The value of this constant is given by,*

$$S_{Cutoff} = \mu + \frac{\Sigma_{12} + \Sigma_{\theta_1}}{\Sigma_{12}} \left\{ [\frac{a + (N-2)K - (N-1)K_2}{N}]^2 - [\frac{a + (N-2)K - NK_2 + K_1}{N+1}]^2 \right\}. \quad (8)$$

Proof: *It is easy to see that* $\Delta\Pi(S)$ *is decreasing in S. Thus, we can derive the value of* S_{Cutoff} *by solving the equation* $\Delta\Pi(S_{Cutoff}) = 0$.

Lemma 4 illustrates the main impact of adding uncertainty to the model economy. While before we concluded that fraud always results in an increase in firm value to all remaining rivals, here we see that the revelation of fraud may actually lower rival firm value. This will be the case if the information from the announcement of fraud is sufficiently bad that it results in a higher assessment of the industry-wide cost component. Note that a higher value of the signal, *S*, implies more negative information because it represents, on average, a higher cost of production.[5]

The benefit of the model is that we can now use Lemma 4 to derive several testable cross sectional implications. Below we describe these implications explicitly and explain the intuition behind each of them.

Implication 1 *The announcement effect is more likely to result in a drop in the value of the rival firm (* $\Delta\Pi < 0$ *), Firm 2, whenever the fraud firm is smaller and has less assets,* A_1.

The larger A_1 is the larger will be the minimum required signal for which rival firm value declines. Thus, higher assets imply a larger range of signals for which rival firm value will

[5] The uncertainty in the model is uncertainty about the fixed cost of production. This is chosen for ease of calculations. In an earlier version of the paper we assumed uncertainty with respect to aggregate industry demand, *a*. The results in both versions of the model were essentially the same and hence we chose to use this formulation which is slightly less cumbersome mathematically.

increase. The intuition for this is that the larger the fraud firm the more other firms stand to gain from its demise.

Implication 2 *The announcement effect is more likely to result in a drop in value ($\Delta\Pi < 0$) for firms in industries that are more competitive (larger N).*[6]

The result follows from the fact that S_{Cutoff} is increasing in *N*. The intuition for this is that the more competitive the industry the smaller the benefit to the remaining firms from the demise of the fraud firm.

Implication 3 *The announcement effect is more likely to result in a drop in value ($\Delta\Pi < 0$) whenever the initial uncertainty regarding the fraud firm is smaller (i.e., the variance of the idiosyncratic component Σ_{θ_1} is smaller).*

The intuition for this result is that the more uncertainty we have about the fraud firm the less informative the signal that the fraud generates. Hence, investors are less likely to use it heavily when updating their lowered expectations of Firm 2's value.

Implication 4 *Firm 2's value is more likely to decrease upon the announcement of fraud when there is more uncertainty about the rival firm (i.e., Σ_{12} is higher).*

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[6] For the analysis of this implication we make the simplifying assumption that $K_2 = K$. With this assumption the cutoff value simplifies to, $S_{Cutoff} = \mu + \frac{\Sigma_{12} + \Sigma_{\theta_1}}{\Sigma_{12}} \left\{ [\frac{a-K}{N}]^2 - [\frac{a-2K+K_1}{N+1}]^2 \right\}$. In addition, because of the restriction on K_1 we have that $(\frac{a-K}{N})^2 > (\frac{a-2K+K_1}{N+1})^2$ and the result follows.

The more uncertainty there is about the rival's costs the more important the (negative) signal to the updated valuation. Thus, the more likely it is that the value of Firm 2 will drop. This result is in essence the counterpart to the previous implication.

Implication 5 *The larger S is the more likely it is that the announcement will lead to a drop in the value of the rival firm.*

This implication simply states that the larger the magnitude of the (negative) news about the fraud firm the larger will be the (negative) spillover to the rival.

IV. *Data and empirical results*

In this section we describe our data, formulate the tests and discuss the empirical results.

IV.1. *Data*

Our sample consists of all competitors of firms accused of committing fraud. To identify the firms accused of fraud we search all SEC Accounting and Auditing Releases (AAERs), in the period between January 1995 through June 2005, for the occurrence of the word "fraud" that relates to misrepresentation of the firm's financials.[7] We also use the business section in Factiva to complement the information obtained from the AAERs. Namely, we search Factiva's news

[7] The process leading to the publication of an AAERs is described in detail in Dechow, Sloan and Sweeney (1996) and Feroz (1991).

section to identify the date in which the market learns about the fraud.[8]

Initially, we identify 642 reports of allegations of fraud against firms and their executives. For some firms we identify multiple reports of federal proceedings relating to the same event, and therefore we eliminate any duplicate releases. As described in Karpoff et al. (2007), the discovery period precedes the enforcement. Thus, to identify the day when the allegation of fraud becomes publicly known we search the Factiva database for the earliest record of the occurrences of the word “fraud”, “accounting errors”, “misstatements”, “accounting investigation” or any combinations of the above that relate to incidences of financial misrepresentation.[9] The date of this earliest record is then used as the fraud revelation date.

To be included in our sample, we require the availability of CRSP data for the fraud firm surrounding the time of the fraud date. This restriction reduces the sample to 111 fraud firms. For 8 of these firms we do not have enough observations to compute abnormal returns and hence we delete these firms whenever fraud firm abnormal returns are included.[10]

We follow Lang and Stutz (1992) in identifying the fraud firm’s industry rivals based on the four digit SIC code.[11] The 111 fraud firms are relatively evenly distributed across the 70 different industries. As shown in Table 1, there are between 1 and 2 fraud firm per industry with

[8] AAERs capture over 80% of the cases of financial fraud (see Karpoff, Lee and Martin 2007). One advantage of using the AAERs is that the SEC takes action mostly in cases where the fraud is significant and the misconduct is intentional. This is important because often financial restatements are the result of technical mistakes or misinterpretations of the accounting standards and, hence, less than 40% of these cases result in litigation (see Palmrose and Scholz 2004). An alternative approach, used by Gande and Lewis (2007), is to collect information from the Stanford database about shareholders’ lawsuits. Our method seems to lead to a similar sample of firms once we eliminate lawsuits that are not related to earnings fraud.

[9] Examples are self disclosed internal investigations, usually accompanied by restatements of earnings and management resignations, and delayed filings followed by shareholders’ lawsuits, analysts’ downgrades, change in auditors, informal SEC investigations publicly disclosed by the firm.

[10] In the analysis where the dependent variable is the rival firm, we lose another 3 events because the rival firms do not have CRSP data available.

[11] Servaes and Tamayo (2006) identify competitors using a list of the largest competitors published by S&P which turns out to be similar to limiting the sample to the largest competitors using Compustat data on firms in a particular SIC.

one exception where there is a concentration of 18 fraud events in the software industry (although they are spread across a ten year period). In the robustness section we show that the results remain the same whether or not we include these frauds in our sample.

Table 1 also shows that there is an average of 9.25 fraud events per year with a max of 27 in year 2002 (following the collapse of Enron). We also find that fraud firms are large relative to their rivals with an average size of $7.6bn relative to $2.6bn, as measured by book value of assets. Finally, fraud firms in our sample have an average of 42 rivals with a minimum of one and a maximum of 481 (banking). For this reason we also do a robustness analysis (where possible) in which we first average the rival response for each fraud event and then take the average across these events thus giving an equal weight to each fraud event regardless of the number of rivals.

IV.2. *Variables and hypotheses*

Testing the predictions of the model requires the construction of several variables that proxy for the competition effect and for the contagion effect.

To measure the impact of the announcement of fraud on the fraud firm and its rivals we use the standard event study methodology (Dodd and Warner (1983)) and estimate expected returns using the value-weighted CRSP index and data from 255 to 46 days before the revelation date. Cumulative abnormal returns (CARs) are then calculated as the difference between the event period return and the market model expected return.

We use two variables to measure the impact of competition. First we construct a Herfindahl index to proxy for industry concentration. The Herfindahl index is calculated based on sales of the firms in the same four-digit SIC code. A higher index number represents a more concentrated industry which implies that rivals in that industry stand to benefit more from the fraud firm's reduced ability to compete.

A second measure relating to the competition effect is the size of the fraud firm which we measure using the log of sales of the fraud firm (Sales FF). We expect to find a positive relation between the size of the fraud firm and the rival's CAR because rivals have more to gain from the demise of a large fraud firm then they have from the demise of a small fraud firm.

The information effect depends on several fraud firm and rival firm characteristics. As a first measure of the information content of the announcement we use the 21 day CAR of the fraud firm (CAR FF). Implication 5 suggests that more (bad) news about the fraud firm will affect the industry rivals more negatively.

To measure information uncertainty we use the market-to-book ratio of the fraud firm and of the rival (MB FF and MB Rival). A higher MB is a proxy for higher uncertainty. Higher uncertainty about the fraud firm should result in higher rival announcement returns as the market will tend to discount noisier information when updating valuations. In contrast, Implication 3 suggests a negative relation between rival firm uncertainty and rival CAR. Thus, more uncertainty about rival valuation should result in lower rival announcement returns as there will be more updating of firm value from any external (negative) fraud firm announcement.

As an alternative measure of rival firm uncertainty we use the root mean square error (RMSE) from the market model regression using daily returns from 255 to 46 days prior to the fraud announcement. The market return is the value-weighted CRSP index. A higher RMSE indicates more valuation uncertainty, hence a higher likelihood that information coming from the fraud firm will be used to update the rivals' valuation.

A third measure of information asymmetry is the number of analysts following the fraud and the rival firm. This measure is computed using data from IBES for the subsample of our firms with analyst following. We define a dummy variable, *D Analyst Following FF*, equal to one if the fraud firm has more analyst coverage than the median fraud firm in our sample.[12] We expect a negative relation between analyst following of the fraud firm and rival CARs because less coverage of the fraud firm should lead to noisier information and hence less updating of rival value. Similarly, we create a dummy variable, *D Analyst Following Rival*, equal to one if the number of analyst following a rival firm is higher than the industry median. A larger number of analysts should lead to less valuation uncertainty and, hence, to a lower impact from the negative information spill over.

As a more direct measure of the information flow between the fraud firm and its rivals we use the Earnings Response Coefficient (ERC). The ERC measure that we compute is a historical value that captures how the *rival* firm's market value changed in response to the *fraud* firm's past earning surprises. This is different from the standard ERC used in the literature (e.g., Collins and Kothari, 1989; Kothari and Sloan, 1992). The ERC is calculated based on quarterly information about earnings surprises of the fraud firm during the three-year period before the revelation of fraud. We use the following regression specification:

$$CAR_{ijt} = a_{ij} + b_{ij} UE_{jt} + e_{it} ,$$

where CAR_{ijt} is the cumulative abnormal return of rival i in the five days around the earnings announcement of fraud firm j in quarter t and UE_{jt} is the unexpected earnings announcement (earnings surprise) of fraud firm j calculated in quarter t. The earnings surprise is computed as

[12] We get qualitatively similar results if we define the dummy equal to one if the fraud firm has more analyst following than the industry median firm in that year (not reported for brevity).

the difference between the analyst consensus quarterly earnings estimate and the realized earnings as reported in IBES. The slope coefficient b_{ij} is the earnings response coefficient (ERC), estimated for each rival *i* of fraud firm *j*. This variable conveys information about the extent to which the valuation of firm *i* depends on information available about firm *j*.

We create a dummy variable, *D ERC*, equal to one if the rival ERC is larger than the median rival ERC within the same event (which in this case is also the median industry ERC). A higher ERC indicates that the rival firm reacted more to past earning surprises of the fraud firm. Thus, potentially, investors have used the fraudulent accounting information of the fraud firm to update the price of the rival firm. Consequently, we expect a negative relation between *D ERC* and CAR rival as the fraud revelation requires investors to revise their valuation of the rival firm more significantly.

Finally, we control for the size of the rival firm defined as the log of rival sales (Sales Rival). While not directly linked to our model this variable may reflect the level of asymmetric information in which case we would again expect a positive relationship with the announcement return.

IV.3 *Results*

Before analyzing the stock price response of rival firms to the announcement of fraud we first look at the cumulative abnormal return (CAR) of the fraud firm around the announcement date.

IV.3.1 *Fraud firm CAR*

Figure 1 shows that fraud firms, on average, suffer a negative CAR (-36% in the -10 to +10 day period) surrounding the revelation date. As the figure indicates, the revelation date identified by our procedure is preceded by negative fraud firm stock returns suggesting that there is some information leakage prior to the revelation date. For this reason we use a 21-day window around our event date in the multivariate analysis (the results are robust to different event windows as further discussed in the robustness section).

In Table 2 we look at the response of rival firms to the announcement of fraud and report the average CAR for the rivals for different event windows. The main result is that, on average, rivals experience a decrease in their value when information about the fraud firm is released. This is true for various event windows as well as when calculating the average rival CAR using equal weighting (Panel A) or when first averaging the rival response for each fraud event and then taking the equal weighted average of all 111 events (Panel B). Note that excluding the frauds in the software industry results in a less negative average rival CAR. This is consistent with our expectation as this industry is very competitive.

IV.3.2 *Extreme portfolio analysis*

The theoretical analysis of the impact of fraud on rival firms suggests the existence of both a competition and an information effect. To obtain a sense of the cross sectional variation in rival reaction we report in Table 3 the average rival response for various “extreme” portfolios. These extreme portfolios are formed based on characteristics that our model predicts should result in a positive rival CAR and those that predict a negative rival CAR.

To form these portfolios we sort all rival firms into quintiles based on several characteristics and report the average CAR for these rival firm portfolios. In panel A of Table 3, we show average rival CAR for the subsamples that are in the top (high expected announcement) and bottom (low expected announcement) quintile of these characteristics.[13] Namely, for each characteristic the rival firm is given a score from 1 to 5 depending on which quintile it is in. Then for each set of characteristics we sum up the score of each of the rivals and report the average CAR of all rivals with the highest three scores and with the lowest three scores.

For example, looking at the first row of Panel A we find that there are 121 rival firms that have a combined score of 5, 6, or 7. These rivals are predicted to have the lowest CAR because they are from the most competitive industries, are rivals of small fraud firms who had a very negative CAR, and they also have a high MB ratio, and the lowest sales. For this group of rivals we find an average CAR of -11.94%. Conversely, using the same characteristics we find that the high score sample, (i.e., the firms with a score of 25, 24, or 23) consists of 115 firms whose average CAR is +4.51%.

In panel B of Table 3 we repeat the analysis by forming the two extreme portfolios based on whether or not a firm is in the top or bottom 10% of the sample. We rank each rival based on the relevant characteristic and give it a score from 1 to 5 (according to quintile cutoffs and predictions of the theory). Then we add the scores across the characteristics and take the top and bottom 10% of the sample firms. The findings, again, confirm that the low score subsamples have negative average abnormal returns while the subsamples with the high score have (mostly) positive abnormal returns. For example, the first row, which is based on the same characteristics

[13] The top (bottom) quintile is defined relative to the theoretical prediction. For example, a high value of MB Rival is expected to be correlated with lower rival CAR. Hence, the quintile containing rivals with the highest MB is labeled as the 'bottom quintile' with a score of 1.

as in panel A, now contains 783 firms that have an average CAR of -2.80%. In contrast, the high score subsample contains 810 firms that have an average CAR of 0.86%.[14]

In sum, we find large differences in rival CARs between the high and low score portfolios highlighting the fact that there is significant cross sectional variation in how rivals are affected by the fraud. Thus, while empirically we find that the average rival suffers a value loss; our model is helpful in identifying how each individual rival is affected by the revelation of fraud.

IV.3.3 *Multivariate analysis*

As the above results are univariate in nature we conduct additional multivariate tests to measure the marginal impact of each of the fraud firm and rival firm characteristics on the rival's value (i.e., CAR). In Table 4 we report the results of OLS regressions, where the dependent variable is the rival CAR and the independent variables are different rival and fraud firm characteristics that are predicted by the model to have an impact on rival value. To compute the standard errors, we use the Huber-White[15] sandwich estimator that corrects for the possibility that the errors are not independently and identically distributed. In section 4.4.3., we also show robustness using between-effects regressions that especially correct for the possible lack of independence of the observations.

The results are consistent with the model's predictions. For example, in Column 1 of Table 4 we include two variables that measure the extent of the competition effect and several variables that measure different aspects of the information effect. We find that the Herfindahl index is positively related to rival CAR. This is consistent with the argument that rivals in more

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[14] The fact that the samples are not exactly 10% of the total sample is due to the discreetness of the score that goes from 5 to 25.
[15] Based on Huber (1967) and White (1980).

concentrated industries stand to gain more from the fraud. The coefficient on the Herfindahl variable is 0.021 which implies that rival firms in the highest Herfindahl industry (Petroleum) have, on average, a 14.1% higher CAR relative to rivals from the lowest Herfindahl industry (Commercial Banks). We also find that rivals of larger fraud firms experience a higher announcement return. This is consistent with the argument that the potential exit of a larger fraud firm leaves more surplus to be shared by its competitors.

In Column 1 of Table 4 we also report results for several information variables. In particular, we find a positive and significant coefficient on CAR FF, and MB FF, and a negative and significant coefficient on MB Rival. The positive coefficient on CAR FF indicates that more (negative) information about the fraud firm leads to more (negative) updating of rival firm value. In terms of economic significance, a one standard deviation drop in fraud firm value reduces rival firm value, on average, by 2.36%. The positive coefficient on MB FF indicates that more uncertainty about the fraud firm results in less updating of the rival firm's value based on this information. The negative coefficient on MB Rival indicates that when there is more uncertainty about the rival the market uses any external information more heavily to update the rival's value. Finally, although our model does not have a direct prediction on the variable of rival sales (the derivative with respect to rival size cannot be signed) we find a positive and significant coefficient on this variable. This, perhaps, indicates that there is less uncertainty about the valuation of larger rivals or that they are better positioned to increase their hold on the industry.

In Column 2 we replace MB rival by RMSE rival and use it as an alternative measure of uncertainty. While the main conclusions relating to our hypotheses stay the same the coefficient on the variable of rival sales becomes insignificant. This is probably due to the high correlation between RMSE and size which is -0.47.

In Column 3 of the table we include several additional measures of information using analyst data. In particular, we include three variables: the indicator of the earnings response coefficient, the number of analysts following the fraud firm, and the number of analysts following the rival. While this reduces the size of our sample, we find that all previous variables remain significant (apart from CAR FF). In addition we find that D ERC is negative and significant which is consistent with the interpretation that rivals whose value was more affected by past earning surprises reported by the fraud firm are now suffering a larger drop in value. Finally, both analyst variables fail to be significant, again, probably due to the smaller sample size.

For this reason we take out the ERC variable in Column 4 and find that the dummy variable, *D Analyst following FF*, is negative and significant. This gives further support to the argument that more uncertainty about the fraud firm results in a higher rival CAR.

In the last specification of the table (Column 5) we include an interaction variable between D Herf and Sales FF, where D Herf is a dummy variable equal to one if the industry in which the fraud occurred has a Herfindahl index above the median of the 111 events. We find that rival firms benefit from the fraud especially if the fraud firm is large and if the industry is highly concentrated. In addition, we find that firm size plays an insignificant role in competitive industries as evidenced by the insignificant coefficient. This is entirely consistent with the competition hypothesis.

In sum, the results of the multivariate analysis are all consistent with the predictions of the model and illustrate the exact way in which the combination of the negative information spillover effect and the positive industry competition effect impact each individual rival.

IV.4 *Robustness*

In this section we conduct several tests to illustrate the robustness of the empirical results to alternative specifications.

IV.4.1 *Repeated frauds within an industry*

Because there are repeated frauds in the software industry (SIC code 7372) as well as to a lesser extent in several other industries, we conduct a robustness test to verify that the results are not driven by a particular industry. To this end we run our base line multivariate specification (column 1, Table 4) for a subsample of rivals of all fraud events that are not preceded by another fraud event in the same industry within the three months prior to the fraud date (this restriction eliminates most multiple industry frauds leaving us with 89 fraud events with available data). Column 1 in Table 5 reports the results from this regression that contains 5776 rival firms. The results remain significant and with the predicted sign, which suggests that they are not driven by any particular industry.[16] In further, untabulated tests, we find that using only the very first fraud in an industry (in our database) leaves the results unchanged.

IV.4.2 *Equally weighting fraud events*

Each fraud firm can have a vastly different number of industry rivals. For this reason our cross-sectional analysis puts more weight on those fraud firms that have more rivals. To address this point we repeat the analysis and use each fraud event as one unit of observation by estimating between group estimators using a fixed effects framework (e.g., Greene, p. 618 ff).

[16] Gande and Lewis (2007) have shown that the announcement return of a fraud firm does not reflect the full extent of the fraud if the firm is in an industry in which previous frauds have occurred. While our robustness test controls for this effect it is not necessarily clear why this would be a concern for our cross-sectional results.

This is known as the "between-effects" regression that is a cross-sectional regression where the dependent and independent variables are the averages of the variables for each fraud event. For example, if a fraud event is associated with 20 rival firms then each dependent variable associated with this fraud will be the average of the 20 rival firms. Hence, the regression is based on the number of fraud events in our sample and thus allocates equal importance to each of the events, independent of the number of rival firms associated with the fraud firm.

The main conclusions drawn from this regression framework, presented in Columns 2 and 3 of Table 5, remain the same. However, the coefficient on MB FF in Column 3, where we use RMSE Rival as a proxy for rival uncertainly instead of MB Rival, loses statistical significance while still being of the predicted sign.

IV.4.3 *Different event windows*

The analysis so far has focused on a 21-day event window to compute the abnormal announcement returns for fraud and rival firms. We re-run our regressions using a shorter event window of +/- 5 days and obtain qualitatively similar results as shown in Columns 4 and 5 of Table 5.[17]

IV.4.4. *Alternative measures of the impact on rivals*

Our analysis so far has focused on the change in the rival's stock return around the announcement of the revelation of fraud by the fraud firm. While this measure captures the market's expectation of the future impact of fraud on today's rival value, we can also look at some additional measures of the long-term (six month and one year) changes occurring to rivals.

[17] The one exception is that in Column 5 the coefficient on rival sales loses significance, but our model does not have a prediction on this variable.

In what follows we look at two such measures, namely the change in realized market share and the change in expected earnings.

IV.4.4.1 *Changes in market share*

One measure of the long-term effect of fraud is the change in a rival firm's market share. This measure is particularly useful to investigate the competition effect and less so the information effect. We calculate the change in the rival's market share as the difference between the rival's market share in the four quarters prior to the fraud revelation and the four quarters after fraud starting with the quarter of the fraud revelation. The total market size is based on sales information about firms listed in Compustat.

In Table 6, we report results of OLS regressions where the dependent variable is the change in the rival's market share. In Column 1 the independent variable is the industry concentration which has a positive and significant coefficient. This finding supports our model's implications because rivals in more concentrated industries benefit more from the fraud by expanding their market share. In Column 2 we find that this coefficient remains significant even after controlling for the rival's and the fraud firm's lagged market share (in the year prior to the fraud). As implied by our model, we also find that the larger the lagged market share of the fraud firm the larger the gains in market share to the rival firm. Finally, in Column 3 we show that the impact of the fraud firm's lagged market share is positive and significant only for fraud firms in concentrated industries. This suggests that in competitive industries it is hard for rivals to gain much from the demise of the fraud firm even if it is large.

IV.4.4.2 *Changes in expected earnings*

One would expect that changes in expected earnings of rivals would reflect both the competition and the information effects. To analyze changes in the rival's expected future earnings we calculate for each rival firm the change in its one year ahead earnings-per-share (EPS) forecast in the seven month period around the fraud revelation date. In untabulated tests we find that the rival's average one year ahead EPS forecast decreases by about 10% (statistically significant). More importantly, the change in EPS forecast is positively correlated with the Herfindahl index. Interestingly, we also find that the change in EPS is positively and significantly correlated with rival CAR (correlation coefficient of 0.05) suggesting that analysts also update their valuation in accordance with the market.

IV.4.5 *Fraud versus bankruptcy*

Although the work of Lang and Stulz (1992) on bankruptcy focused mostly on an industry level analysis it is important to see whether or not our fraud firms are different than firms that declare bankruptcy. To obtain a clearer picture of what happens to our sample of fraud firms we use the delisting codes in CRSP and find that out of the 111 fraud events, 62 firms (55%) are still active two years after the fraud revelation, 45 are delisted, and 5 are taken over. Thus, our fraud event is not simply a declaration of bankruptcy but rather represents a completely different corporate event. Hence, our analysis provides valuable information on how a fraud event, rather than a bankruptcy event, propagates across the industry.

IV.4.6 *Aggregate value impact of frauds*

Finally, to see the aggregate effect of fraud on the value of the industry as a whole we compute the dollar change in market capitalization of all rival and fraud firms. Figure 2 displays the market value loss in the 21-day period surrounding the fraud announcement by Herfindahl deciles. The highest deciles reflect concentrated industries while the lowest reflect the most competitive industries.

The main result from the figure is that there is an aggregate value loss of about $950 billion in competitive industries (first 3 deciles) which is substantially more than the cumulative losses of the fraud firms in those deciles (adding up to about $50 billion). In contrast, rival firms in the three highest Herfindahl deciles gain about $30 billion in market capitalization which is about the same amount lost by the fraud firms in those industries. This suggests that investors in concentrated industries would not be affected by the fraud of one firm in the industry as long as they hold an industry portfolio.

V. *Conclusion*

This paper is the first to study the larger impact of a fraud by one firm on the market as a whole. In particular, we study how fraudulent earnings manipulation by one firm affects its rivals. Our results highlight the fact that while, on average, rival firms also suffer from the announcement of fraud there is significant cross sectional variation in this effect. We demonstrate on a firm level basis which firms stand to gain and which firms stand to lose.

In sum, the analysis furthers our understanding of the broader impact of fraud while at the same time providing strong evidence that the market incorporates information about the fraud firm into its valuation of the industry and of the individual rivals of the fraud firm.

Appendix A

Proof Lemma 1: From the first order condition we have that for each Firm i $q_i + K_i = q_2 + K_2$.

Additionally, for Firm 2 we have that $q_2 + K_2 = P \equiv a - \sum_{i=1}^{N} q_i$. Thus, replacing each of the

q_i's and rearranging yields the result. Deriving the profit is a simple calculation of the maximization problem at the optimal quantity. QED

Proof Lemma 3: Let $F(K_1) \equiv (q_2^{**})^2 - (q_2^{*})^2$. It is easy to verify that $\frac{dF(K_1)}{dK_1} < 0$ and hence there exists a $\overline{K_1}$ such that for $K_1 < \overline{K_1}$ $F(K_1) > 0$. Replacing the equilibrium values of q_2^{*} and q_2^{**} in to the inequality $F(K_1) > 0$ it is easy to show that the function is positive as long as

$K_1 < \frac{a + (N-2)K + K_2}{N}$ which by Assumption 2 is the condition needed for the quantity produced by Firm 1 to have a positive value. QED

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Figure 1
Abnormal announcement returns of fraud firms

The figure presents the average cumulative abnormal return (CAR) around the announcement of fraud for all 111 fraud firms. The abnormal returns are computed using a market model with the value weighted CRSP index as the market. Parameters are estimated over the 255 to 46 days prior to the announcement day. The announcement day, day zero, represents the first day where we find news in Factiva about an alleged fraud.

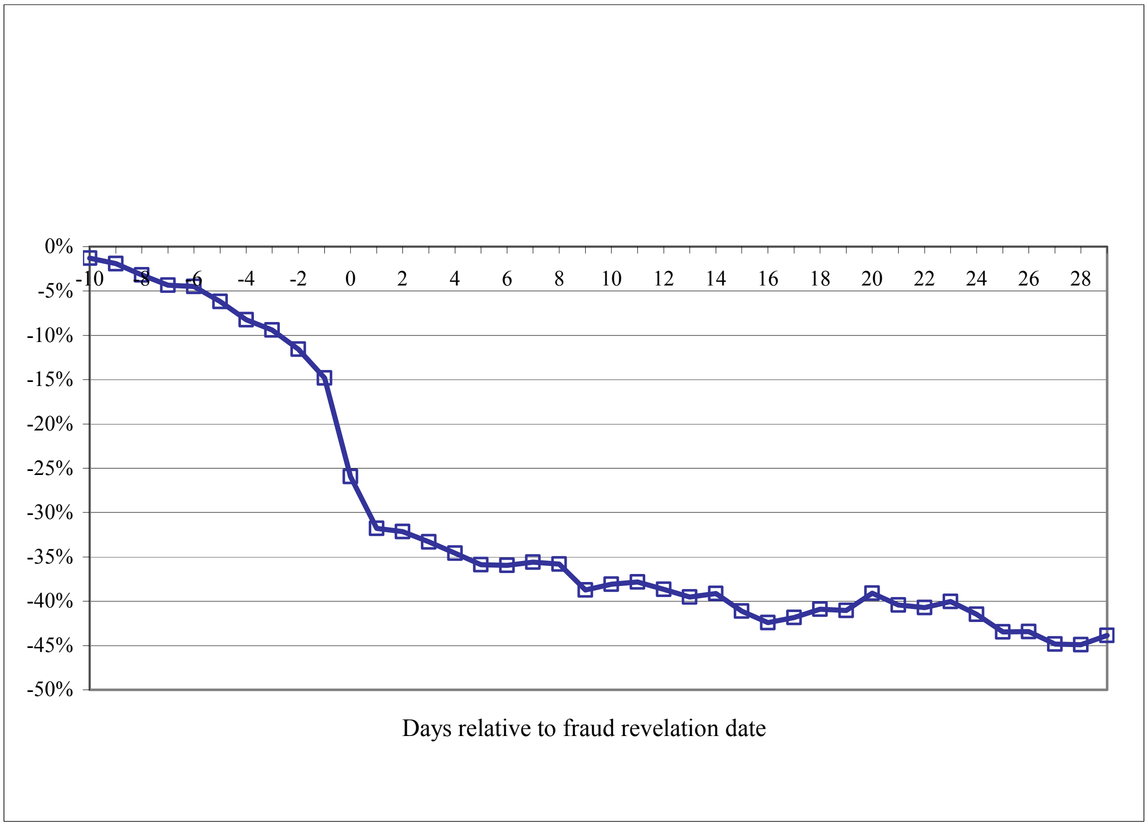

Figure 2
Aggregate industry change in market value by industry concentration

The figure shows aggregate (abnormal) changes in market value in the 21 days around the fraud revelation for fraud and rival firms. The aggregate market value change is computed as the cumulative abnormal announcement return (CAR) times the market value eleven days prior to the revelation date for each firm. The market value changes are then added up across firms in the same Herfindahl decile. Herfindahl deciles are formed based on the 111 fraud events.

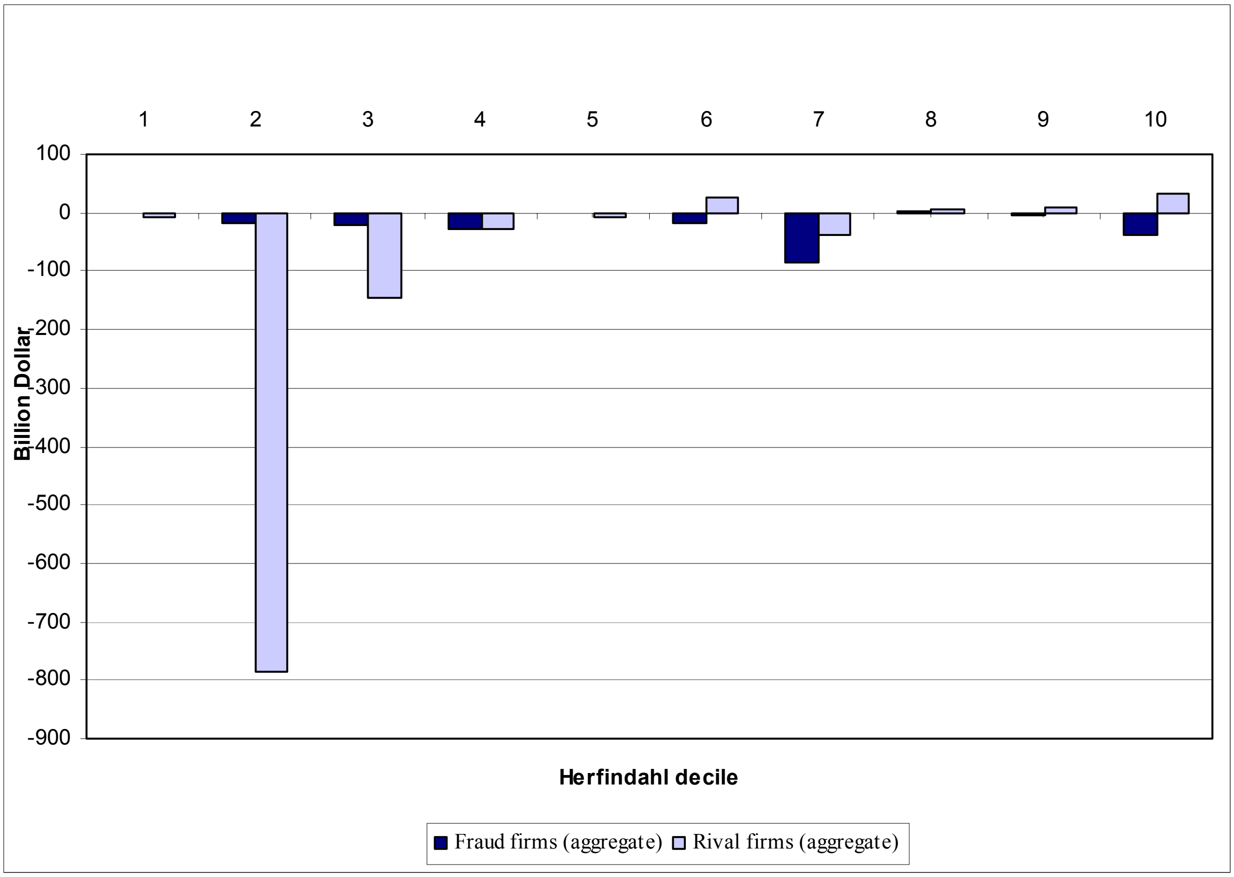

Table 1
Summary statistics

The sample of firms involved in accounting fraud is initially collected from the Accounting and Auditing Releases from January 1995 through June 2005, whereas the alleged fraud period ranges from 1993 to 2004. Each enforcement action can result in several federal proceedings, and therefore we eliminate the duplicate releases relating to the same event and firm. The discovery period precedes the enforcement, and therefore we proceed by identifying the first allegation of financial fraud by searching all news in Factiva database for the word "fraud", "misstatement", "accounting errors", "accounting investigations" or any other association with financial misrepresentation. Many companies are already delisted when the allegations become public, which prevents us from obtaining a price market reaction. After restricting the search to the set of companies with available data in CRSP data base, we remain with 111 fraud firms. The table reports mean, minimum, maximum and total for various variables. Total is the sum over all fraud or rival firm variables, respectively.

	Mean	Minimum	Maximum	Total
Number of Frauds per year	9.25	1	27	111
Number of Frauds per Industry	1.59	1	18	111
Number of Rivals per Fraud Event	42	1	481	10,385
Fraud Firm Size (Assets, bn)	7.6	<0.001	101	658
Rival Firm Size (Assets, bn)	2.6	<0.001	751	5,326

Table 2
Rival firms' abnormal returns

This table presents the mean cumulative abnormal return of the fraud company rivals around the public announcement of the allegation of accounting fraud. Rivals are identified based on the four digit SIC code reported the year before the announcement. We follow the standard event study methodology (Dodd and Warner, 1983) to compute abnormal returns as the share price response to the news over the market model as the pricing benchmark, using the value weighted index. The market model parameters are estimated using one year of trading data ending 46 days prior to the announcement. Positive: Negative shows the relative number of positive versus negative price reactions to the news. Both the parametric t-statistic and the nonparametric z-statistic for the significance of the cumulative abnormal returns are presented. In panel A, the averages are formed giving each rival firm observation the same weight. In panel B, we first equally weight the rival firm's abnormal return within the fraud event and then take the equally weighted average across the fraud event's average rival abnormal returns. The symbols $, *, **, denote statistical significance at 10%, 5%, 1% levels, respectively.

Panel A: Rival firm observations are equally weighted

Subgroups	Windows	Number of obs.	Mean cumulative abnormal returns	t-statistic		Wilcoxon Z statistic		Positive: negative
All rivals	(-3;+3)	10385	-1.38%	-9.758	**	-9.157	**	4453:5932
	(-10; +10)	10385	-2.34%	-7.065	**	-7.049	**	4453:5932
All rivals except software industry	(-3;+3)	4251	-0.96%	-7.307	**	-7.439	$	1847:2403
	(-10; +10)	4251	-1.09%	-3.794	**	-4.454	*	1847:2403
Only software industry	(-3;+3)	6134	-1.68%	-6.614	**	-5.721	**	2596:3537
	(-10; +10)	6134	-3.20%	-6.033	**	-5.465	**	2606:3527

Panel B: Equally weighted portfolios of rivals by event

Subgroups	Windows	Number of obs.	Mean cumulative abnormal returns	t-statistic		Wilcoxon Z statistic		Positive: negative
All rivals	(-3;+3)	111	-0.71%	-1.966	$	-1.849	$	48:63
	(-10; +10)	111	-2.00%	-2.859	*	-2.946	**	39:72
All rivals except software industry	(-3;+3)	93	-0.56%	-1.966		-1.200		42:51
	(-10; +10)	93	-1.82%	-2.819	*	-3.274	**	32:61
Only software industry	(-3;+3)	18	-1.51%	-1.510	$	-1.872	$	6:12
	(-10; +10)	18	-2.70%	-2.700		-1.398	$	7:11

Table 3

Abnormal returns for various portfolios of rival firms

The table shows the average cumulative abnormal returns (CAR), measured in the 21 days around the announcement date using the market model and the value weighted CRSP index as a benchmark, for the rivals included in two extreme portfolios. Each row shows the characteristics upon which the extreme portfolios are constructed. All observations are split into quintiles based on certain characteristics. These characteristics are: the Herfindahl index, defined as the squared sum of the fractions of industry sales, by year. Industry is defined by the four digit SIC code reported on the year prior to the announcement. The size of fraud firm (Sales Fraud Firm) and rival firm (Sales Rival) is extracted from Compustat in the year before the announcement. CAR FF is the cumulative abnormal return of the fraud firm calculated in the 21 days around the announcement. MB FF (MB Rival) is the market to book ratio of the fraud firm (rival) calculated one year before the event. RMSE Rival is the root mean square error of residuals from the market model regression. D ERC is a dummy equal to 1 if the rival earnings response coefficient (ERC) is larger the median ERC within the same event (i.e., the industry). It is calculated based on 3 years of quarterly information on earnings surprises prior to the event. D Analyst Following Rival is a dummy variable equal to 1 if the rival has more analysts that the median industry level (or event level) and zero otherwise. D Analyst Following FF is a dummy variable equal to 1 if the fraud has more analysts than the median fraud firm number of analysts and zero otherwise. A score of 1 is assigned to the lowest quintile of Sales FF, CAR FF, MB FF and a score of 5 to the highest quintile. A score equal to 1 is assigned to the highest quintile created based on Analyst FF and 5 to the lowest. The score equal to 1 is therefore assigned to the group of rivals that is predicted by our theory to have a positive correlation with CAR Rivals. The entire sample (10,385 obs) is also split into quintiles based on the rival characteristics, using the same approach. Note that the split in quintiles is not recursive- the entire sample is split into quintiles based on one characteristic at the time. In Panel A, the portfolios are formed over the lowest (highest) three cumulative scores. Panel B shows the average CAR of all portfolios of rivals with lowest and highest cumulative scores, such that the total number of rivals included in such portfolios is about 10% of the total sample.

Panel A

Characteristics used to create subgroups										CAR Rival (Low score)	Number of firms in the bucket	CAR Rival (High score)	Number of firms in the bucket	Total sample size
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival						-11.94%	121	4.51%	115	8324
Herfindahl	Sales FF	Sales Rival	CAR FF		RMSE Rival					-13.99%	98	0.62%	168	8837
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival	RMSE Rival					-15.58%	60	3.06%	79	8324
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF				-11.10%	110	5.20%	95	8324
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF	ERC			-15.21%	44	6.82%	60	3360
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF		Analysts rival		-10.98%	87	2.85%	113	8324
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF			Analysts FF	-14.42%	98	2.06%	143	4933

Panel B

Characteristics used to create subgroups										CAR Rival (Low score)	Number of firms in the bucket	CAR Rival (High Score)	Number of firms in the bucket	Total sample size
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival						-2.80%	783	0.86%	810	8374
Herfindahl	Sales FF	Sales Rival	CAR FF		RMSE Rival					-6.40%	902	2.22%	865	8899
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival	RMSE Rival					-7.45%	805	1.58%	837	8374
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF				-8.50%	835	1.49%	835	8374
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF	ERC			-16.70%	335	-0.27%	338	3381
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF		Analysts rival		-9.48%	831	3.82%	830	8374
Herfindahl	Sales FF	Sales Rival	CAR FF	MB Rival		MB FF			Analysts FF	-15.51%	452	0.09%	496	4964

Table 4
Multivariate analysis

This table reports results of OLS regressions with Huber-White adjusted standard errors. The dependent variable is the cumulative abnormal return of the rival, 21 days around the announcement date, using the market model and the value weighted CRSP index as a benchmark. The Herfindahl index is defined as the squared sum of the fractions of industry sales, by year. Industry is defined by the four digit SIC code reported on the year prior to the announcement. The size of fraud firm (Sales Fraud Firm) and rival firm (Sales Rival) is extracted from Compustat on the year before the announcement. CAR FF is the abnormal return of the fraud firm calculated 21 days around the announcement. MB FF (MB Rival) is the market to book ratio of the fraud firm (rival) calculated one year before the event. RMSE Rival is the root mean square error of residuals from the market model regression. D ERC is a dummy equal to 1 if the rival earnings response coefficient (ERC) is larger the median ERC within the same event (i.e., the industry). It is calculated based on 3 years of quarterly information on earnings surprises prior to the event. D Analyst Following Rival is a dummy variable equal to 1 if the rival has more analysts that the median industry level (or event level) and zero otherwise. D Analyst Following FF is a dummy variable equal to 1 if the fraud has more analysts than the median fraud firm number of analysts and zero otherwise. D Herf is a dummy variable equal to 1 if the fraud firm is in an industry where the Herfindahl is above the median fraud firm's Herfindahl, and 0 otherwise. Robust p-values are in parentheses: * significant at 5%; ** significant at 1%.

Dependent Variable:	CAR Rival[-10,+10]				
	(1)	(2)	(3)	(4)	(5)
Herfindahl Index /1000	0.021	0.026	0.039	0.026	
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	
Sales Fraud Firm	0.005	0.006	0.016	0.009	-0.001
	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.459)
Sales Rival	0.005	0.000	0.008	0.006	0.006
	(0.001)**	(0.864)	(0.000)**	(0.011)*	(0.000)**
CAR FF	0.083	0.084	-0.019	0.035	0.080
	(0.000)**	(0.000)**	(0.209)	(0.002)**	(0.000)**
MB FF	0.004	0.002	0.011	0.008	0.004
	(0.000)**	(0.014)*	(0.000)**	(0.000)**	(0.000)**
MB Rival	-0.005		-0.003	-0.005	-0.004
	(0.000)**		(0.000)**	(0.000)**	(0.000)**
RMSE Rival		-0.939			
		(0.000)**			
D ERC			-0.042		
			(0.000)**		
D Analyst Following Rival			-0.005	0.004	
			(0.668)	(0.633)	
D Analyst Following FF			-0.001	-0.059	
			(0.944)	(0.000)**	
Sales Fraud Firm * D Herf					0.019
					(0.000)**
D Herf					-0.054
					(0.001)**
Constant	-0.064	-0.013	-0.257	-0.107	-0.016
	(0.000)**	(0.502)	(0.000)**	(0.000)	(0.195)
Observations	8322	8835	2794	4246	8819
R-squared	0.039	0.03	0.069	0.046	0.032
Number of fraud events	100	100	55	62	100

Table 5
Robustness tests

This table reports robustness tests. Columns 1, 4, and 5 are OLS regression with robust standard errors. Columns 2 and 3 show results of between-effects (BE) models, using a weighted least square estimation to adjust for unbalanced data. Regression 1 includes only rival firms of the first fraud event in an industry unless the next fraud is more than three months later. Regressions 2-5 use all rival firms with available data again. The dependent variable in regressions 1-3 (4 and 5) is the cumulative abnormal returns of the rival, 21 (11) days around the announcement date using the market model and the value weighted CRSP index as a benchmark. The Herfindahl index is defined as the squared sum of the fractions of industry sales, by year. Industry is defined by the four digit SIC code reported on the year prior to the announcement. The size of fraud firm (Sales Fraud Firm) and rival firm (Sales Rival) is extracted from Compustat on the year before the announcement. In regressions 1-3 (4 and 5) CAR FF is the abnormal return of the fraud firm calculated 21 (11) days around the announcement. MB FF (MB Rival) is the market to book ratio of the fraud firm (rival) calculated one year before the event. RMSE Rival is the root mean square error of residuals from the market model regression. Robust p-values are in parentheses: $ significant at 10%, * significant at 5%; ** significant at 1%.

Dependent Variable:	CAR Rival [-10,+10]			CAR Rival [-5,+5]	
	(1)	(2)	(3)	(4)	(5)
Herfindahl Index /1000	0.022	0.017	0.028	0.007	0.008
	(0.000)**	(0.041)*	(0.001)**	(0.000)**	(0.000)**
Sales Fraud Firm	0.005	0.008	0.013	0.002	0.002
	(0.000)**	(0.071)$	(0.015)*	(0.060)$	(0.005)**
Sales Rival	0.003	0.030	0.036	0.002	-0.000
	(0.057)$	(0.026)*	(0.018)*	(0.042)*	(0.69)
CAR FF	0.029	0.104	0.092	0.017	0.017
	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
MB FF	0.003	0.011	0.004	0.003	0.002
	(0.073)$	(0.001)**	(0.222)	(0.000)**	(0.000)**
MB Rival	-0.004	-0.021		-0.001	
	(0.000)**	(0.000)**		(0.000)**	
RMSE Rival			-3.268		-0.433
			(0.001)**		(0.000)**
Constant	-0.077	0.124	0.238	-0.04	-0.013
	(0.000)**	(0.046)*	(0.013)*	(0.000)**	-0.172
Observations	5776	8322	8835	8320	8833
R-squared	0.027	0.352	0.276	0.01	0.01
Number of fraud events	89	100	100	100	100

Table 6
Change in market share of rivals

This table reports the results of OLS regressions with Huber-White adjusted standard errors. The dependent variable is the change in market share of the rival firm. The independent variables are: the Herfindahl index, the lagged market share of the fraud firm, and that of the rival firm. The market share change is calculated as the difference between the market share before and after the event. Market share is computed on an annual basis using the four quarter of sales before and after the event date. The quarter when the fraud is revealed is included in the calculation of the market share after the event. $, *, ** indicate significance at the 10%, 5%, 1% level, respectively.

Dependent Variable:	Change in market share of rival		
	(1)	(2)	(3)
Herfindahl Index /1000	0.001	0.000	
	(0.005)**	(0.011)*	
Lag market share rival		-0.008	
		(0.672)	
Lag market share FF		0.029	-0.009
		(0.000)**	(0.571)
D Herf			0.000
			(0.064)$
D Herf * Lag market share FF			0.020
			(0.064)$
Constant	0.000	0.000	0.000
	(0.040)*	(0.026)*	(0.055)$
Observations	9795	9396	9396
R-squared	0.005	0.041	0.04
Number of fraud events	111	106	106