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Stock Market Trading in the Aftermath of an Accounting Scandal

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Abstract

In this paper, I study the impact of fraud revelation on trading behaviour of investors. I ask if investors with direct exposure to stock market fraud (treated investors) are more likely to cash out of the stock market than investors with no direct exposure to fraud (control investors)? Using daily investor account holdings data from the National Stock Depository Limited (NSDL), the largest depository in India, I find that treated investors cash out almost 10.6 percentage points of their overall portfolio relative to control investors post the crisis. The cashing out is largely restricted to the bad stock. Over the period of a month, there is no difference in the trading behaviour of the treated and control investors. This paper, for the first time, is able to capture trading behaviour on a daily basis for an extended period of time instead of basing the analysis on household survey data, or observing investors at monthly or yearly frequency.

Keywords: fraud; stock market trading; individual investors; India
JEL: D1; G1; G3

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1 Introduction

Research on investor participation in financial markets shows that investors personal experiences play a disproportionate role in shaping their risk appetite and consequently their trading decisions (Kaustia and Knupfer, 2008; Malmendier and Nagel, 2011; Malmendier and Nagel, 2016; Anagol, Balasubramaniam, and Ramadorai, 2015; Andersen, Hanspal, and Nielsen, 2016). Investors react to major shocks (such as the 2008 financial crisis) through a change in risk perceptions that affects trading decisions (Dorn and Weber, 2013; Hoffmann, Post, and Pennings, 2013).

What we do not have adequate evidence for is how a "firm-specific governance" shock affects investment behaviour, especially of small investors in emerging economies which are generally characterised by low participation, low financial literacy, and a larger trust deficit.[1] Behavioural biases such as too much trading, over-confidence, trading on attention-grabbing stocks or a disposition effect (Odean, 1998; Barber and Odean, 2000; Barber and Odean, 2001; Barber and Odean, 2008) may get exacerbated for such investors in the event of a firm specific governance shock.

Studying firm-specific shock is important for three reasons. First, a firm-specific shock is unanticipated for the most skilled household trading in the market. Second, when the shock is on account of " poor governance", it forces investors to pay attention to governance issues. And third, it creates an environment where investors may extrapolate their experience - if one firm had poor governance standards, might other similarly placed firms be the same?

There is an emerging strand of literature that has begun to estimate the impact on investor behaviour of fraud revelation. Gurun, Stoffman, and Yonker (2015) exploit the collapse of the multi-billion dollar Ponzi scheme orchestrated by Bernard Madoff, and find that residents of communities that were more exposed to the fraud subsequently withdrew assets from investment advisers and increased deposits at banks. Similarly, Giannetti and Wang (2016) find evidence that a one-standard-deviation increase in fraud revelation intensity in a state during a year leads to a 0.4 percentage point decrease in the households equity holdings with huge implications for cost of capital.

In this paper, I use a remarkable natural experiment to obtain evidence about fraud revelation and stock market participation. I ask, if investors with direct exposure to firm-specific fraud are more likely to cash out of the stock market than investors with no direct exposure to fraud? Is this behaviour restricted to the stock in question, or is

[1] The World Values Survey evidence shows that low income countries have lower levels of trust capital.

there an effect on other stocks? How does this behaviour vary with degree of exposure, experience in markets, and proximity to the epicenter of the fraud? I also ask if the reaction to fraud is an immediate response or continues to persist over long horizons?

I narrow my attention to a single event, the biggest, and most unexpected accounting fraud in the Indian stock market, also known as the "Enron of India". On 7 January 2009, the chairman of one of the most successful IT companies, Satyam, confessed that he had manipulated the accounts of the firm by US$1.47 billion. Investors in Satyam are said to have lost almost Rs.136 billion (US$2 billion) over the next month. While Satyam had been in the news in the previous month over its acquisition of two real-estate companies (Maytas Properties and Maytas Infrastructure), the scale of the accounting fraud was entirely unexpected, and a complete surprise (Wharton, 2009).

The data on daily investor account holdings comes from the National Securities Depository Limited (NSDL), the largest depository in India in terms of total assets tracked (roughly 80%). I am thus able to capture trading behaviour immediately after the event, and on a daily basis for an extended period of time unlike other papers that base their analysis on household survey data, or observe investors at monthly or yearly frequency.

I focus on investors who held Satyam shares in their accounts one day prior to the event, and compare them to those who did not have such exposure. The selection on observables problem is overcome by using a matching framework. Matching procedures are preferable to randomly selecting investors with no exposure to Satyam as they are less likely to lead to estimation bias by picking investors with completely different characteristics.

I find that investors with direct exposure to Satyam trade more intensely immediately i.e. over seven days after the Satyam event relative to control investors, and that this trading was largely driven by *cashing out* of the portfolio. Treated investors cash out almost 10.6 percentage points of their overall portfolio relative to control investors post the crisis. The cashing out is largely restricted to the "bad stock". If anything, treated investors make *net purchases* of related stocks during the same period. Over the period of a month, there is no difference in the trading behaviour of the treated and control investors. The results are robust to comparison with days of similar portfolio losses, and dealing with rumblings on the Satyam stock a few weeks prior to the scandal.

These results are contrary to international evidence in two respects. First, the results show that the effect is restricted only to those investors and stocks that were the subject of the governance fraud, unlike results from the US which show that households withdraw from unrelated stocks as well as from the asset class itself. Second, the results show that the effect is attenuated over time. Results from the US indicate that effects of fraud are long-lasting (Gurun, Stoffman, and Yonker, 2015; Giannetti and Wang, 2016). Of course, instances of fraud may deter participation on the extensive margin, and cause fewer people to enter the market, but data restrictions prohibit us from throwing light on this important question.

The type of fraud, and the cultural and institutional settings in which the fraud takes place may vary across locations, and possibly explain the differences in the results with the international literature. In order to understand the impact of firm specific fraud revelation, and the channels through which it manifests, it is important to build up a literature that analyses such events across multiple settings. This paper is the first, to the best of my knowledge, to focus on the impact of fraud in an emerging market. The literature on limited participation in emerging economies, especially India, has so far focused largely on supply side challenges i.e. the problems in the distribution of retail financial products (Anagol and Kim, 2012; Halan, Sane, and Thomas, 2014; Halan and Sane, 2016). The paper by studying investor reaction to fraud, presents evidence on the demand side.

The paper proceeds as follows. In Section 2 I describe the data, and in Section 3 the research design including a discussion of the fraud, as well as the estimation methodology. In Section 4 I discuss the results, and heterogeneous treatment effects in Section 5. Section 6 describes the robustness checks. Section 7 concludes.

2 Data

The data is sourced from India's National Securities Depository Limited (NSDL), the largest depository in India in terms of total assets tracked (roughly 80%). Even though equity securities can be held in both dematerialised and physical form, most stock transactions take place in dematerialised form.

While this dataset is similar to that of (Campbell, Ramadorai, and Ranish, 2013), it differs in two important respects. First, I have daily holdings data for each investor, as opposed to monthly holdings data. This is an important difference, as it allows me to evaluate changes to account balances immediately after any event, which is difficult to do with a monthly aggregation. Second, the data extends beyond 2012, till 2016. For the rest, I have similar limitations on demographic information provided, namely, that I am not able to identify actual age, gender, or any other household information.

In this dataset a single investor can hold multiple accounts. However, I am able to merge all accounts with a single Permanent Account Number (PAN) number,[2] to arrive at an estimate of one account per investor. I also focus on those accounts that have at least one equity ISIN listed in NSE in their portfolio. As of 6 January, 2009, the day before the Satyam crisis, there were 5.6 million individual accounts in NSDL.

Districts in the states of Gujarat, Maharashtra, Karnataka, Andhra Pradesh (now bifurcated to Andhra Pradesh and Telangana) and Tamil Nadu have about 3% or more accounts which held Satyam stocks as of the date of the crisis. The districts with the largest proportion of Satyam holders include Rangareddi (3.08%), Dakshin Kannada (2.96%), Hyderabad (2.889%), Chennai (2.56%), Bangalore (2.55%), and Mangalore (2.52%). It is useful to note that all of these are districts in South India, in regions close to the headquarters of Satyam in Hyderabad.

I focus my attention on the analysis of a stratified random sample of investors from the NSDL universe. The sample is created as follows. I have randomly selected drawing 20,000 individual accounts from each Indian state with more than 20,000 accounts, and all accounts from states with fewer than 20,000 accounts. I have additionally sampled 4000 Satyam holders from each state, and a total sample of 439,461 investors. The investors are retail participants with Indian domicile and not foreign and institutional participants.

I then remove observations whose portfolio value as of 6 January, 2009 is greater than a Rs.1 million. This gives me a sample of 423,362 investors. Of these, 10% or 40,461 investors held Satyam shares prior to the crisis date.

Table 1 shows the summary statistics of Satyam and non-Satyam holders. Satyam holders are a little more experienced than non-Satyam holders – the average number of years they have been in the market is 4.5 as opposed to 3.7, statistically significant at the 1% level. Satyam holders also have higher portfolio values prior to the crisis than non-Satyam holders, and also trade larger quantities. Satyam holders also had been making net purchases into the portfolio over the 30-day period prior to the crisis. The Satyam group has a lower portfolio beta, and lower portfolio returns than the other group - perhaps a result of trading higher quantities. These differences underscore the need for a matching framework.

[2]The PAN is a unique identifier issued to all taxpayers by the Income Tax Department of India, and is mandatory at the time of account opening at NSDL.

Table 1 Sample summary statistics as on January 6, 2009

The table presents the average values of account characteristics between investors who held Satyam shares and investors who did not. The numbers in the bracket indicate the standard deviation. For example, the average account age of non-Satyam owners was 3.7 years, while that of Satyam owners was 4.5 years. Total traded value is calculated as the total traded value over the last 30 days. Net traded value is calculated as the difference between buy and sell value over the last 30 days. Portfolio returns are calculated from the previous day i.e. 5 January 2009.

	Does not own Satyam	Owns Satyam	Overall
Account age	3.67	4.64***	3.75
	(2.86)	(2.54)	(2.59)
Total traded value (Rs.000) between $t-30$ and t	5.51	25.82***	7.45
	(77.64)	(94.67)	(79.65)
Net traded value (Rs.000) between $t-30$ and t	-1.05	2.57***	-7
	(75.14)	(68.33)	(74.5)
Portfolio value (Rs.000)	81.44	210.27***	93.75
	(145.48)	(227.09)	(159.71)
Portfolio returns between $t-1$ and t	-0.09	-0.29***	-0.11
	(0.04)	(0.37)	(0.13)
Portfolio Beta	0.88	0.85***	0.87
	(0.31)	(0.23)	(0.30)
Has other IT stocks	0.18	0.58***	0.22
	(0.49)	(0.38)	(0.41)
N	382,901	40,461	423,362

*** indicates statistically significant at 1% level

3 Research design

The central problem in identifying the causal impact of fraud on stock market participation is that fraud may occur at the beginning of a down-turn, and this may independently drive households to reduce their investments in equities (Wang, Winton, and Yu, 2010). One therefore requires the unraveling of a fraud that was not unearthed because of a down-turn. Another problem in identification is that the results may be driven by differences in the treated and control investors.

I begin by presenting the context of the occurrence of fraud and make the case that this was a complete surprise, and not driven by the 2008 downturn. I then turn to deriving a sample where I control for selection on observables.

3.1 The Satyam fraud

When India emerged out of its license raj, into a post-liberalised era in the early the 1990s, the software revolution played an important role in integrating India to globalisation. Satyam, based in Hyderabad, the capital of the then state of Andhra Pradesh[3] was an IT company that offered software development, system maintenance, packaged software

[3] The state has recently split into Telangana and Andhra Pradesh.

integration and engineering design services. By 1999, Satyam Infoway, a subsidiary of Satyam, had become the first Indian IT company to be listed on Nasdaq. Satyam had also expanded its footprint to 30 countries. In 2007, the promoter of Satyam, was named the Ernst & Young Entrepreneur of the Year. By 2008, Satyam's revenues had crossed almost $2 billion. Satyam's promoter was the poster boy of India's IT revolution.

On January 7, 2009, the chairman of Satyam publicly confessed that he had manipulated the accounts of the firm by US$1.47 billion (Joseph, Sukumar, and Raghu, 2009). Later investigations revealed that the top management had fudged the company's books by overstating its revenues, profit margins and profits for every single quarter over a period of five years, from 2003 to 2008. At the same time, both Satyam's internal as well as statutory auditors had not brought these discrepancy's to light (Krishnan, 2014).

The month of December 2008 had seen several rumblings about Satyam. First, there was the event of the acquisition of two real-estate companies (Maytas Properties and Maytas Infrastructure), followed by exits by independent directors.[4] However, none of these problems had suggested the scale of the accounting fraud, which was entirely unexpected (Wharton, 2009).

I confirm this by Figure 1 which shows a comparison of Satyam as against the NSE-Nifty market index. The top panel shows the daily close price, obtained from the NSE. The bottom panel shows the realised volatility. [5] In the appendix, I show the comparison of Satyam with its top competitors in the IT sector.

The graphs suggest that there was nothing hugely different about the trading of Satyam stock. If anything for a few days before, the Satyam stock was trading at a higher price than its competitors. The stock was also not differentially affected by the global financial crisis either - in fact, the company was doing fairly well, and its stock price was stable. Before the announcement, on the morning of the 7th September, 2009, there was no inkling that such a news was expected, either on the overall Nifty index, or on Satyam and its competitors.

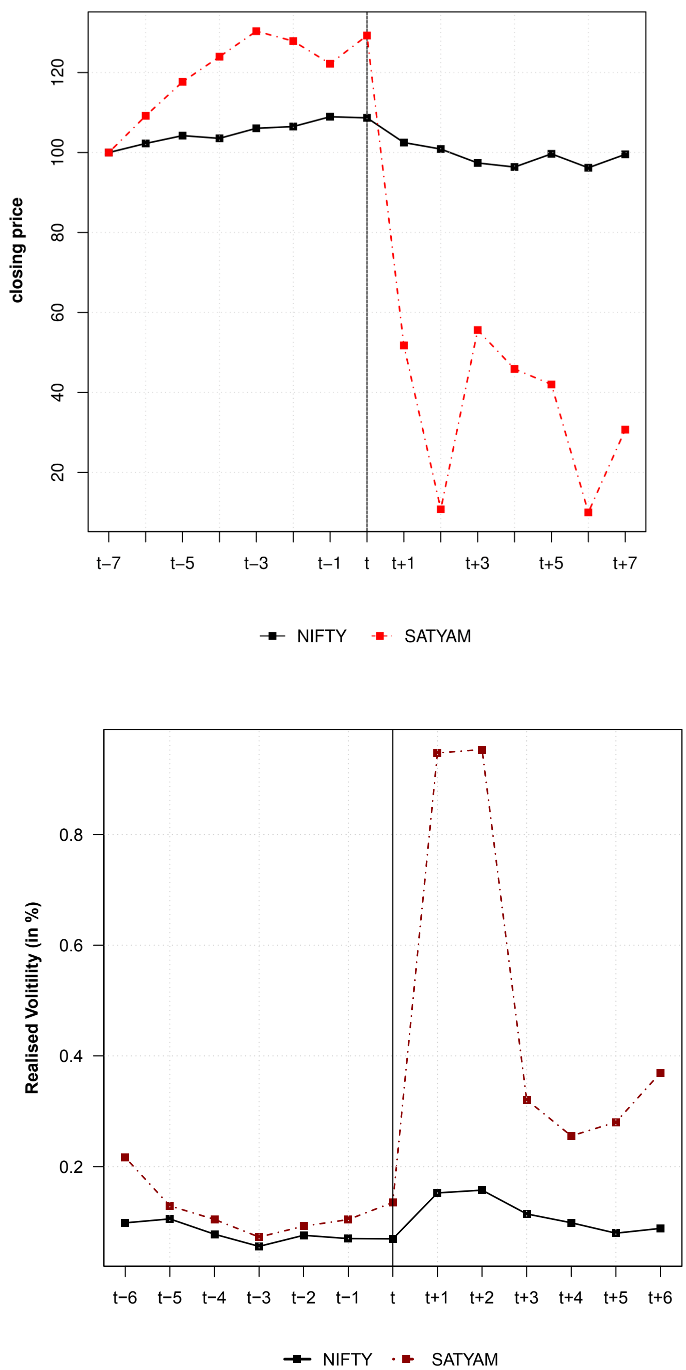
The disaster was a result of an accounting fraud and is said to have had serious ramifications on investor confidence. It was believed that the promoter of Satyam had betrayed the trust of his employees, the IT industry and a whole nation that looked up to him (D'Monte, 2014). Both Satyam's internal as well as statutory auditors had not brought

[4]A date-wise summary of events is provided in the Appendix.

[5]This is computed using intraday returns of a stock at NSE aggregated at 12 second frequency. I split the entire day's trading time into 5 minute windows and compute the standard deviation of returns of the stock in all windows. The mean of all the standard deviation values is considered the daily realised volatility of the stock.

Figure 1 Close price and realised volatility of Nifty

This figure shows a comparison of Satyam as against the NSE-Nifty market index. The top panel shows the daily close price, obtained from the NSE. The bottom panel shows the realised volatility. This is computed using intraday day returns of a stock at NSE aggregated at 12 second frequency. I split the entire day's trading time into 5 minute windows and compute the standard deviation of returns of the stock in all windows. The mean of all the standard deviation values is considered the daily realised volatility of the stock.



these discrepancy's to light, and Satyam was seen as a failure of the system - of auditors, or the board, of the regulator, leading to a loss of trust in the system itself (Krishnan, 2014). Soon after the chairman's confession, the price fell to an all-time low of Rs 6.30. Investors in Satyam are said to have lost almost Rs.136 billion (US$2 billion) over the next month.

The Serious Fraud Investigation Office (SFIO), the multi-disciplinary investigating arm of the Ministry of Corporate Affairs, set up in 2003 with officials from various law enforcement agencies, was asked to investigate the fudging of accounts. It submitted its preliminary report on April 13, 2009. The Raju brothers were subsequently booked for criminal breach of trust, cheating, criminal conspiracy and forgery under the Indian Penal Code. At the same time, the company was bought by Tech Mahindra.[6]

In January 2018, the capital markets regulator, the Securities and Exchange Board of India (SEBI), finally passed an order where it found Price Waterhouse guilty barred its network entities from issuing audit certificates to any listed company in India for two years. SEBI also ordered disgorgement of over Rs.130 million (USD 2 million) on account of wrongful gains from the audit major and its two erstwhile partners who worked on Satyam accounts.[7] This reaffirms the view that the scandal was a result of the accounting fraud and not directly influenced by the financial crisis.

3.2 The matching framework

To test the hypothesis I require a counter factual of the investors' stock market participation in the absence of exposure to Satyam. This is best done using a matching framework where I match investors on observables that determine the choice of holding of Satyam prior to the crisis. Matching procedures are preferable to randomly selecting investors with no exposure to Satyam as they are less likely to lead to estimation bias by picking investors with completely different characteristics.

As the event was completely exogenous and unexpected, I use the nearest neighbour matching with the Mahalonobis distance measure. In its simplest form, 1:1 nearest neighbor matching selects for each treated unit i the control unit with the smallest distance from individual i. The Mahalanobis distance measure is calculated as follows:

$$D_{ij} = (X_i - X_j)'\Sigma^{-1}(X_i - X_j)$$

[6]This is a joint venture between India's Mahindra Group and U.K.'s BT Group.
[7]`https://goo.gl/3hNt5T`

where D_{ij} is the distance between unit i and j and X_i and X_j are the characteristics of the control and treatment units. In our case, the treatment group consists of investors who held Satyam stock in their portfolio one day prior to the fraud announcement, while the control group consists of those who did not have prior direct exposure to Satyam.

The focus of this paper is the impact of fraud on investor behaviour. It is, therefore, important to control for similarities in investor characteristics. Since I do not have access to demographic details of the investors, I use details related to investment behaviour that are accessible using holding data of the accounts prior to the Satyam event. The observables for the matching exercise include:

Age of the investor : Experienced investors in India have a lower portfolio turnover, exhibit a smaller disposition effect, and invest more heavily in value stocks than novice investors (Campbell, Ramadorai, and Ranish, 2013). It is possible that older investors, measured in the number of years since first purchase in the stock market, are more resilient in the face of crisis, and have a better judgment about the overall status of the market.

Trading intensity : Research has shown that investors that engage in active trading earn lower returns (Barber and Odean, 2000; Barber et. al., 2009). It is possible that active investors also react to the "bad news" faster than "buy-and-hold" investors. I therefore measure the traded value in the last 30 days prior to the Satyam event.

Portfolio beta : This captures the idiosyncratic share of portfolio variance and investors with a high beta portfolio are more likely to be under diversified. This is an important metric that captures investor behaviour. It is likely that investors with a high beta are more exposed to fewer stocks, and more likely to react to news of a fraud than investors with a low beta. I measure beta by a market model with the value-weighted universe of Indian stocks as the market portfolio (Campbell, Ramadorai, and Ranish, 2013) as of 6th September, 2009.

Log portfolio value : This captures the value of the investors portfolio. Investors with a larger portfolio value may feel less perturbed by the Satyam fraud, relative to smaller portfolios. I match the investors on log of the portfolio value measured as of the 6th September, 2009.

The matching methodology described so far gives me 40,461 control observations (i.e. those who did not hold Satyam in their portfolio) for an equal number of treated observations (i.e. those who held Satyam stock prior to the crisis).

Table 2 Match balance: t-stat, standardised difference and ks-stat

This table presents the match balance statistics between the treatment and control group. t-stat and p-val are generated from the t-test, SDIFF reflects the standardized difference.

	(1) Means Treated	(2) Means Control	(3) SD Control	(4) Mean Diff	(5) t-stat	(6) p-val	(7) SDIFF	(8) ks-stat	(9) p-val
Portfolio beta	0.85	0.89	0.29	-0.05	-0.23	0.82	-0.16	0.002	0.00***
Log (portfolio value)	11.46	10.06	17.55	13.98	-0.05	0.96	0.04	0.005	0.59
Net turnover (Rs.)	2576.62	-1052.26	76431.76	3628.87	1.45	0.14	1.02	0.08	0.00***
Account age	4.46	3.67	2.53	0.79	0.0004	0.99	0.0003	0.007	0.34

A fundamental assumption of the matching approach is that conditional on the covariates, the potential outcomes are independent of the treatment. The pre-treatment variables should be balanced between the treated and control investors. Lack of balance points to a possible mis-specification of the matching estimation (Rosenbaum and Rubin, 1983). One therefore needs to verify that this balancing condition is satisfied by the data.

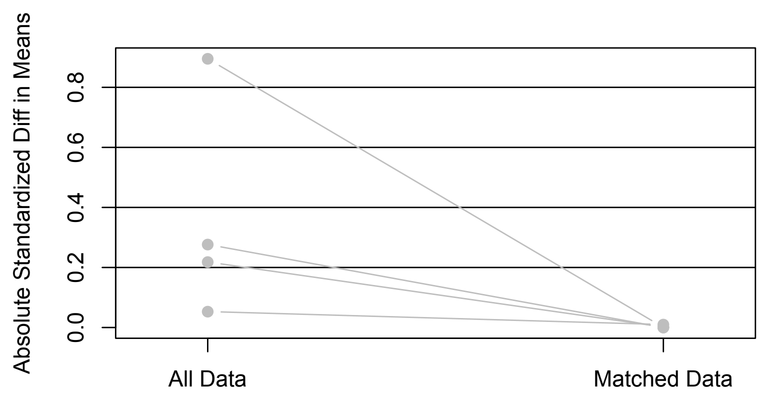
I present results on balance statistics in Table 2. These include the coefficients out of a paired t-test (Columns 5 and 6) and standardised bias (Column 7) for each variable entering the matching model. The standardised bias for the portfolio value variable, for example is defined as the difference in means between treated investors and the appropriately control investors by the average variances of the portfolio value variable in the two groups. I also report the Kolmogorov-Smirnov (KS) test statistic (Columns 8 and 9) which compares two empirical distributions (on the basis of the cumulative distribution function).

The t-stats confirm that there is no significant difference in means between the two groups, while the KS-statistic shows that there is no significant difference in the distributions between the two groups, except for the portfolio beta and net turnover variables. As the t-test does not show a significant difference for all variables, including those for whom the KS-statistic is statistically significant leading me to believe that the balancing conditions are reasonably satisfied for each variable.

The lower the standardised difference, the more balanced the treatment and control groups are for the variable in question. While there is no formal criterion for appropriate value of standardised difference, a value of upto 20 is considered acceptable (Rosenbaum and Rubin, 1985). The standardised difference is well below the limit of 20 for all the match variables. I also present the change in the standardised bias for all the covariates after matching in Figure 2. The standardised bias has fallen dramatically after matching, and I take this as evidence for the existence of a reasonable matched control sample.

Figure 2 Difference in the standardised bias

This figure shows the change in standardized bias after matching. The left hand dots show the standardized bias for the entire data-set, while the right hand shows that for the matched data-set.



3.3 Main outcome of interest

In the event of a large accounting scandal such as the Satyam fraud, I expect that investors are likely to revise (upwards) their mistrust of accounting data, and of the equity market as well. Such increase in mistrust may lead investors to become "once burned twice shy", and cash out of the market. I expect that these effects are likely to be pronounced for investors with direct exposure to the fraud. There are three kinds of withdrawals that are likely:

1. Withdrawal from existing holdings in the market i.e. cashing out of the portfolio
2. Withdrawal from particular sectors, especially those that are likely to be related to the accounting fraud.
3. Complete withdrawal from the market. This could either be in the form of account closure by existing investors, or lack of entry by new investors.

In this paper, I focus on the first two kinds of withdrawals, and provide only descriptive evidence on account exits. I am not able to evaluate the third measure, that is on account opening and closing by investors as there is no household survey data spanning the years of the crisis to measure effects on portfolio allocation of households.

Participation on the intensive margin can be measured using the difference in the daily holdings data of each investor. Several papers that look at investor behaviour have to make inferences using data at intervals such as a month or a year. As a result, they are not able to distinguish between portfolio rebalancing and cashing-in/cashing-out from the portfolio. As I have daily holdings data for each investor, I am able to measure not only the changes in portfolio value, but also changes in the holdings of individual stock. This allows me to focus exclusively on cashing-in and out of the portfolio.

For a two stock portfolio, comprising of stocks A and stock B at any given time t, Cash-in and Cash-out (denoted by Δ_{At} and Δ_{Bt}) is calculated by:-

$$\Delta_{At} = P_{At-1} x Q_{At} - P_{At-1} x Q_{At-1} \tag{1}$$

$$\Delta_{Bt} = P_{Bt-1} x Q_{Bt} - P_{Bt-1} x Q_{Bt-1} \tag{2}$$

P_{it} is the price of the stock "i" in time t and Q_{it} is the weights or the quantity of the stock "i" at time t in the portfolio. The gross traded value or grossΔ is given by:-

$$gross\Delta_t = \sum_A^B |\Delta_{it}| \tag{3}$$

The net traded value or netΔ is given by:-

$$net\Delta_t = \sum_A^B \Delta_{it} \tag{4}$$

The net traded value is thus the difference between the total buy trades made using *new money* and total sell trades *that were not re-invested in another stock* between $t+1$ and t. This captures the *net purchase* element of investor trades, and is a more appropriate measure of the cashing-in (or cashing-out) of the investors portfolio. A positive value indicates that there were net purchases i.e. the investor purchased more securities, while a negative value indicates that there were net sales i.e. the investor sold more securities.

For example, suppose an investor has 10 shares of Company A of Rs.10 each in his portfolio on day t. The portfolio value of this investor is Rs.100. For simplicity, let's assume that the price remains at Rs.10 on $t+1$. Suppose the investor sells the 10 shares of Company A, and buys 10 shares of Company B. The gross traded value here is Rs.200. However, the net traded value is 0, as there would be no new money coming in, or money being taken out. If the investor sold the 10 shares of Company A, and made no other purchase, then the net traded value would be -Rs.100, that is there would be a cashing out of Rs.100 from the portfolio. Similarly if the investor did not sell these 10 shares, and instead bought 10 shares of Company B at Rs.10 each, then the net traded value would be Rs.100, that is there would be a cashing-in into the portfolio.

3.4 Difference-in-difference

The following DID model on the matched sample estimates the causal impact of the Satyam event:

$$y_{i,t} = \beta_0 + \beta_1 \text{SATYAM}_{i,t} + \beta_2 \text{POST-SATYAM}_{i,t} + \beta_3 (\text{SATYAM}_{i,t} \times \text{POST-SATYAM}_{i,t}) + s_i + \epsilon_{i,t}$$

where $Y_{i,t}$ is the net traded value (in Rs.) or the net traded value as a proportion of portfolio value. SATYAM is a dummy which takes value "1" if investor i held Satyam stock (the treated investor) and "0" otherwise (the control investor). POST-SATYAM captures whether the observation is from the period before the Satyam event (post-crisis = "0") or after (post-crisis = "1").

$\hat{\beta}_3$ will be positive and statistically significant if there is greater cashing-in, and negative and statistically significant if there is greater cash-out by the the treated investors after the event compared to the matched control investors. The matching DID estimator considerably improves on standard matching estimators (Blundell and Dias, 2000) by eliminating unobserved, time-invariant differences between the treatment and control groups (Smith and Todd, 2005). It is also an improvement on a simple DID where the treatment and control units may not have match balance.

I use a state fixed effect s_i to control for state-level conditions, which may affect households equity holdings or be correlated with the timing of fraud revelation. I also cluster standard errors at the investor level because an investors decision to hold stocks is likely to be correlated over time.

4 Results

4.1 Effects on cashing out of portfolio

I begin by testing whether the news of fraud has an impact on trading activity beyond the narrow sphere of the stock in question. This is an interesting question because it allows one to study the effect of fraud on trading decisions overall.

Figure 3 plots the total traded volumes by the treated and control investors seven days before and after the Satyam announcement. The left panel plots the total value traded, while the right panel plots the net value traded i.e. the amount investors withdrew from the market. The confidence bands in the graph are created by bootstrapping the values of net and gross traded values separately.[8]

Over the seven days after the crisis, the treated group had a gross traded value of Rs.3.7 billion, while the control group had Rs.1.7 billion. In contrast, in the seven days prior to the scandal, the treated investors' total traded value was Rs.2.4 billion, while that of the control investors was Rs.1.4 billion. Thus, while the treated investors always traded more than the control investors, this differential increased after the Satyam scandal.

The right panel of the figure indicates that the sale of stocks constituted a large part of the trading volumes. The overall net traded value of treated investors over this period was -Rs.2.1 billion, while that of control investors was -Rs.0.8 billion. In contrast, prior to the scandal, both the treated and control investors were "cashing-in".

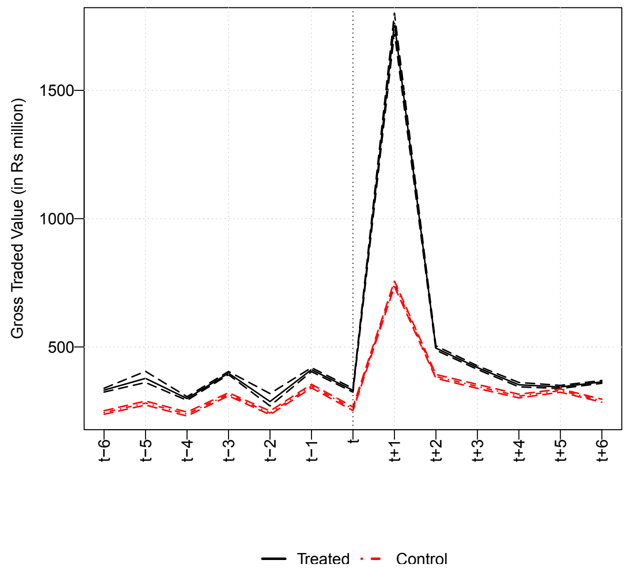
I now ask, what is the average amount of cashing out by such investors? How has this changed after the scandal? The DID regression estimates on the rupee value of net trades (NTV), and NTV a percent of portfolio value are shown in Table 3 in Column (1) and (2) respectively. The treated group is those with Satyam shares a day prior to the event, while the control group is those without Satyam shares. I am interested in the coefficient (β_3) on the Treat*Post interaction term. This gives me the difference between the amount cashed out by treated and control group before and after the event.

Consistent with Figure 3, I find that the average amount traded by treated investors was larger than control investors, even though this was not statistically significantly different when measured as a proportion of portfolio value. I also find that investors cashed out

[8] I bootstrap the daily distribution of the net and gross traded value 1000 times and calculate the sample statistic. The 95% confidence interval bands are obtained by taking the 2.5th percentile and 97.5th percentile values of the resulting distribution of the sample statistic. The process is repeated for all the days i.e +- 7 days to get the 2.5th and 97.5th percentile values of the sample statistic.

Figure 3 Total traded value and net traded value

The graph shows the total traded value and net traded value by treated investors (i.e. those who held Satyam shares) and control investors (matched) seven days before and after the Satyam crisis announcement. The vertical bar marks the date prior to the fraud revelation date.



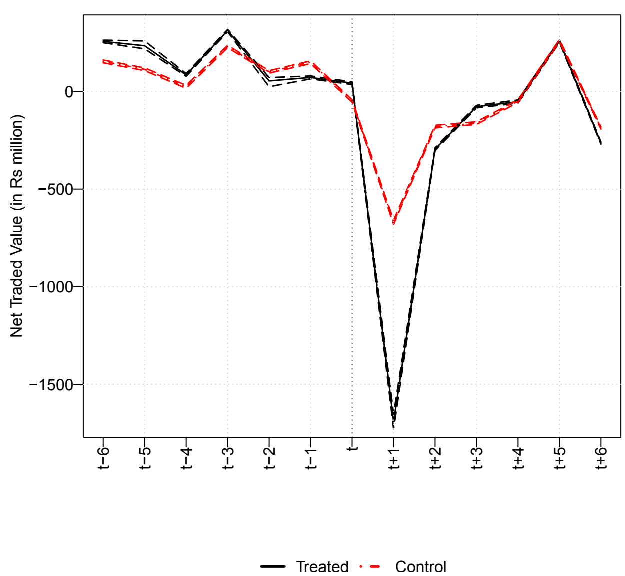


Table 3 Net traded value

The table presents results from a DID regression on net traded value (NTV) and NTV a proportion of portfolio value on 10 days data pre and post the event. The regression reports clustered standard errors at the investor level.

	NTV (Rs.)	NTV/Val (%)
	(1)	(2)
Treat	918.994***	0.5
	(51.821)	(0.7)
Post	−7,380.171***	−3.0***
	(64.490)	(0.9)
Treat*Post	−5,136.610***	−10.7***
	(137.904)	(1.6)
Constant	2,816.367***	−1.9
	(84.548)	(1.5)
State FE	YES	YES
Observations	1,048,090	1,048,090
Note:	*p<0.1; **p<0.05; ***p<0.01	

of their portfolios post the scandal, also consistent with earlier results.

The β_3 coefficient shows that the average amount cashed-out by the treated investors was about Rs.5,137 relative to control investors. This is almost 1.5 times the pre-treatment average of *net purchases* of Rs.3,445. When estimated as a proportion of portfolio value I find that treated investors cashed out 11 percentage points of the portfolio value relative to control investors.[9] The results indicate that the Satyam crisis had a statistically significant impact on cashing-out behaviour of those who held Satyam stock.

4.2 Effects on cashing out of Satyam

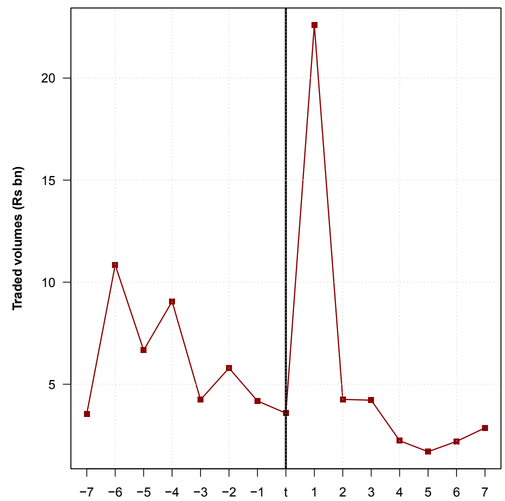
I turn next to evaluating whether the cashing out was driven by the "bad" stock. I evaluate the impact on the Satyam trading activity of the news of fraud. Figure 4, which presents the total traded volumes of Satyam on the NSE, shows a sharp rise one day after the scandal, which subsides after. This suggests that the news of fraud led to a huge reaction on the trading of the Satyam stock.

The Satyam trades of the treated group in the sample were almost Rs.1.4 billion, while the control group were at Rs.36 million. Thus, Satyam trades constituted almost 39% of total traded value of the treated group, and 2% of the control group. The net traded

[9] There is no statistically significant difference in portfolio reallocations between the two investors. The results are available on request.

Figure 4 Total traded volumes (Rs.billion)

The graph shows the total traded volumes on the NSE around the Satyam scandal date.



value on Satyam i.e. the amount of Satyam stock cashed out by treated investors over the 7 days was Rs.1.1 billion. This was 57% of the net traded value, suggesting that a large proportion of the exit by Satyam investors was of the Satyam stock itself.

The control investors actually had a positive net traded value i.e. they "bought" Satyam shares after the scandal worth Rs.17 million. The effect of Satyam was large and negative on the trading behaviour of the treated group. The control group, on the contrary, seems to have seen this as an opportunity to buy some of the depressed stock.

Table 4 presents results from a DID regression on net traded value (in Rs. and as a proportion of portfolio value) of Satyam shares on 7 days data pre and post the event. I find that treated investors, cashed out of their Satyam holdings post the scandal. The β_3 coefficient shows that the differential between the average amount cashed-out by the treated and control investors was about Rs.6,030. This is almost 10 times the pre-treatment average of Rs.583 of *net purchases*.

When estimated as a proportion of portfolio value, treated investors cashed out Satyam shares worth 9.7 percentage points of the portfolio value more relative to control investors. The results indicate that news of a fraud has a significant negative effect on participation in the firm that commits the fraud. When investors heard bad news, their immediate response was to sell shares on the market.

Table 4 Satyam traded value

The table presents results from a DID regression on net traded value (in Rs. and and as a proportion of portfolio value) on Satyam shares on 7 days data pre and post the event. Standard errors are clustered at the investor level.

	STV (Rs.) (1)	STV/Val (%) (2)
Treat	1,306.203***	0.2
	(27.177)	(0.4)
Post	111.582***	−0.2***
	(5.795)	(0.1)
Treat*Post	−6,030.434***	−9.7***
	(110.596)	(0.8)
Constant	−197.793***	−1.9
	(65.362)	(1.3)
State FE	YES	YES
Observations	1,048,090	1,048,090
Note:	*p<0.1; **p<0.05; ***p<0.01	

4.3 Effects on related stocks

An interesting finding of the behavioural finance literature is that investors often extrapolate past events far into the future (Barberis and Thaler, 2003). This is based on the theory proposed by Griffin and Tversky (1992) that one-time strong news events should generate an overreaction as people pay too much attention to the strength of the evidence they are presented with and too little attention to its statistical weight. I, therefore, evaluate the trading behaviour of investors on various groups of stocks that could be related to the Satyam event.

In the eyes of several people, Satyam was a failure of the institutional framework, especially of auditors, and of independent boards to bring accounting discrepency's to light (Krishnan, 2014). If this indeed led to a loss of trust in the entire system, I should see retail investors exiting out of firms that had the same auditor as Satyam (PriceWaterhouse Coopers), and that shared the same independent directors as Satyam.

I find all the companies audited by PriceWaterHouse Coopers India in the year 2007-08 (one financial year prior to the scandal) as per CMIE Prowess.[10] I then subset all such companies listed at NSE for the analysis. I pull out the list of independent directors on Satyam's board on the date of the scandal.

[10]Prowess is a database of the financial performance of over 27,000 companies. It includes all companies traded on the National Stock Exchange and the Bombay Stock Exchange, as well as unlisted public and private companies.

Since the Satyam scandal broke out soon after the knowledge of Satyam's investments into real estate companies (Maytas), other real estate companies, or companies in the same location and industry as a fraudulent firm may often be considered likely to have committed fraud (Gleason, Jenkins, and Johnson, 2008; Goldman, Peyer, and Stefanescu, 2012). I therefore focus on the set of firms headquartered in Hyderabad, as well as Andhra Pradesh, and other firms in the IT industry, and in real estate. These are also pulled out of CMIE Prowess, and the subset of these listed on NSE is used for the analysis.

Table 5 Net traded value on other groups of stocks

This table presents the results of a DID regression on various groups of stocks. Column (1) presents the net traded value of PWC stocks, Column (2) of stocks with other Satyam directors, Column (3) of companies headquartered in Hyderabad, Column (4) of companies headquartered in Andhra Pradesh, Column (5) of real estate companies, and Column (6) of other IT companies. Standard errors are clustered at the investor level.

	PWC	Directors	HQ HYD	HQ AP	Real Estate	IT
	(1)	(2)	(3)	(4)	(5)	(6)
NTV/Val (%)						
Treat*Post	0.3***	0.4***	0.7***	0.7***	−0.2**	0.3***
	(0.1)	(0.04)	(0.2)	(0.2)	(0.1)	(0.04)
Observations	850,848	549,243	646,553	665,817	246,979	703,266
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Note:						*p<0.1; **p<0.05; ***p<0.01

The results are presented in Table 5. Column (1) presents the net traded value of PWC stocks, Column (2) of stocks with other Satyam directors, Column (3) of companies headquartered in Hyderabad, Column (4) of companies headquartered in Andhra Pradesh, Column (5) of real estate companies, and Column (6) of other IT companies.

I find that, contrary to expectations, treated investors actually *cash-in* into stocks of related firms. Even though the coefficients are small, they are statistically significant. For example, treated investors cash-in to the tune of 0.3 percentage points more of portfolio value into other stocks who had PWC auditors relative to the control group.

The only group of companies that seem to have seen exits are real estate companies (Column 5), where treated investors are seen to cash-out to the tune of 0.2 percentage points more of the portfolio value relative to control investors. The results indicate that fraud revelation does not affect all firms, certainly in the short-run, including those that may be seen to have shared characteristics with those that did commit fraud.[11]

[11] In the analysis on the Arthur Andersen shock, Giannetti and Wang (2016) also do not find significant drop in household equity-wealth ratio across specifications, possibly suggesting that while the shock caused some households to exit the stock market, other households were unaffected.

4.4 Effects over time

The results so far have focused on the reaction of investors immediately after the crisis. A related question is if such cashing-out persisted after several days of the event. In Table 6, I present the results of a DID regression, but on 1 month of data pre and post the Satyam event. The period of analysis here is from 2008-11-20 to 2009-02-19. Column (1) presents the results on the net traded value (in Rs.), while Column (2) presents the results on net traded value as a percent of portfolio value.

Table 6 Net traded value (60 days)

	NTV (Rs.)	NTV/portval (%)
	(1)	(2)
Treat	−224.853***	0.6
	(20.754)	(0.6)
Post	−2,089.931***	−2.2*
	(21.048)	(1.2)
Treat*Post	−388.116***	−1.8
	(32.178)	(1.5)
Constant	1,205.814***	−0.7
	(30.802)	(0.6)
State FE	Yes	Yes
Observations	4,884,355	4,884,355
Note:	*p<0.1; **p<0.05; ***p<0.01	

I find no statistically significant difference in the cashing out behaviour (as a proportion of portfolio value) of treated and control investors over a one month horizon. This means that while immediately after the crisis, those exposed to Satyam sold a lot of shares, this behaviour had ceased within one month of the event.

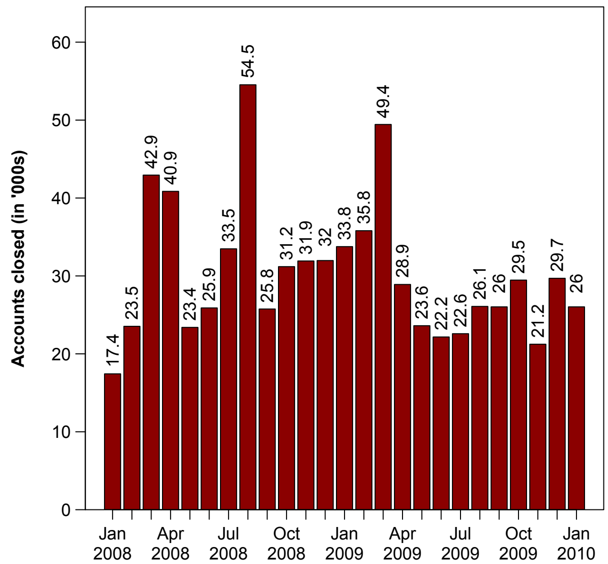
This is contrary to the results of (Giannetti and Wang, 2016) who find large withdrawals by households in equity participation over several years. Our results, however, are consistent with (Hoffmann, Post, and Pennings, 2013) who find that variables quickly recover, and investors continue to trade after the crisis is over.

4.5 Effects on account exits

Previous research on fraud has found that households decrease their stock holdings in fraudulent as well as non fraudulent firms, and even households that do not hold the stocks of fraudulent firms decrease their equity holdings (Giannetti and Wang, 2016).

Figure 5 Accounts closed

The graph shows the total number of accounts closed in the two-year period starting from January 2008 and January 2010.



The measurement on effects on the extensive margin require the use of survey data which capture "all" households, and their investments in "all" financial (and non-financial) instruments. Such regular unit-record level survey data in India is not available. I am, therefore, unable to comment on the effects on the extensive margin. It is also pertinent to note that there were no account closures from the investors in my sample.

I, however, present the data with NSDL on total number of accounts closed in the two-year period starting from January 2008 and January 2010 in Figure 5.[12] I find that there were a slightly larger number of accounts closed in January-March 2009. However, the exits fall within three months to what is a more usual number of exits. The descriptive evidence does not point to large scale exits in the aftermath of the Satyam crisis.

5 Heterogeneous treatment effects

The results so far tell us that there are implications for short-term trading activity, in particular on cashing-out of stock markets, owing to fraud revelation. Exposure to the stock in question has a large, statistically significant effect on cashing out of the market,

[12] This data relates to the entire NSDL universe, and not the sample that is the study of this paper.

largely driven by cashing out of the "fraudulent" stock. I now move to understanding treatment heterogeneity.

5.1 By portfolio value

Table 7 considers how treatment effects vary by portfolio value prior to the crisis. I consider five quintiles of portfolio value. The first quintile corresponds to portfolio value less than Rs.34,000. Portfolio values at 40%, 60% and 80% and 100% are Rs.91,488, Rs.187,032 and Rs.375,739 and Rs.3,685,288 respectively. Column (1) shows the results for the first quintile. Columns (2) - (5) show the results for the second to the fifth quintile respectively.

Table 7 Net traded value by portfolio value

This table presents the DID regression results for each quintile of portfolio value. The quintiles are determined on the basis of portfolio value one day prior to the crisis. The first quintile which includes investors with portfolio value less than Rs.34,000. Portfolio values at 40%, 60% and 80% and 100% are Rs.91,488, Rs.187,032 and Rs.375,739 and Rs.3,685,288 respectively. All standard errors are clustered at the individual level.

	Portfolio value as on 6 Jan, 2009 (Rs.)				
	Q1	Q2	Q3	Q4	Q5
	(1)	(2)	(3)	(4)	(5)
Net traded value / portfolio value (%)					
Treat*Post	-28.0***	-11.0***	-0.3	-0.7	-7.5
	(0.03)	(0.04)	(0.023)	(0.017)	(0.063)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	203334	186620	182786	175253	157728
Note:	*p<0.1; **p<0.05; ***p<0.01				

I find that at the lowest wealth quintile, treated investors cashed out almost 28 percentage points more of their portfolio relative to control investors at the same quintile. At low levels of portfolio wealth, the news of fraud seems to have had a large impact on stock market trading activity.

As the portfolio value increases, the effect attenuates. There may be two reasons for this. At high levels of wealth, the loss from the scandal may be negligible, leading to no reaction. Or, it is also possible that investor portfolio value is correlated with actual wealth, and hence investor sophistication. More sophisticated investors do not react to news of one scandal and are able to withhold from making a panic sale.

5.2 By Satyam exposure

In the class of investors that held Satyam, it is also likely that investors with larger exposure to Satyam would have been more affected. I would expect that cashing out of the stock market, and out of Satyam, would increase with portfolio exposure.

I divide the treated investors into quintiles based on their Satyam exposure one day prior to the scandal. The first quintile's exposure is upto 2% of the portfolio value, the second quintile's is between 2-5%, the third quintile is between 5-10%, the fourth quintile is between 10-32% and the fifth quintile is between 32-100%. I then interact the exposure quintile with the "post" dummy. This allows me to study the relative differences in the trading behaviour of different quantiles after the event.

Table 8 Trading by exposure to Satyam

The table presents results from a DID regression on net traded value (NTV) in Column (1) Satyam stocks (STV) in Column (2), net traded value as a proportion of portfolio value (NTV/val) in Column (3) and Satyam traded value as a proportion of portfolio value (STV/val) in Column (4). Post refers to the period after the Satyam scandal. B2, B3, B4, B5 refer to the second, third, fourth and fifth quintile of Satyam exposure. Standard errors are clustered at the investor level.

	NTV (Rs.)	STV (Rs.)	NTV/Val (%)	STV/Val (%)
	(1)	(2)	(3)	(4)
Post	−3,941.911***	−79.522**	−9.1*	−2.0
	(88.668)	(37.563)	(5.1)	(1.8)
Post*B2	−2,288.990***	−464.079***	1.0	−2.0
	(128.232)	(38.546)	(5.1)	(1.9)
Post*B3	−4,107.557***	−990.240***	−0.7	−4.1**
	(162.174)	(38.526)	(5.1)	(1.9)
Post*B4	−6,351.781***	−2,190.812***	−2.0	−5.2***
	(132.454)	(40.037)	(5.1)	(1.8)
Post*B5	−29,044.280***	−24,986.150***	−21.2***	−25.6***
	(519.158)	(498.061)	(6.3)	(4.0)
Constant	1,523.182***	−56.246	−4.4	−4.1
	(98.178)	(83.754)	(3.4)	(3.3)
Observations	524,616	524,616	524,616	524,616
State FE	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8 presents the results on trading over 7 days of pre and post data. The coefficient on "post" shows the traded value of the first quintile post the Satyam event. Relative to the period prior to the scandal, those with the lowest exposure to Satyam (upto 2%) cashed out an average of Rs.3,942 from their portfolio. This is almost 2.66 times of the net traded value pre-event average of "cashing-in" of Rs.1,479. The same investors cashed out an average of Rs.79 of Satyam shares post the event. This is 3.43 times the pre-treatment average of -23. As a proportion of portfolio value, those with the least exposure cashed out 9.1 percentage points more after the Satyam crisis.

While I find that investors cashed out larger amounts from their portfolios with increase in exposure, the results are not statistically significant when measured as a proportion of portfolio value. Relative to the first quintile, those in the fifth quintile of Satyam exposure, cashed out an average amount of Rs.29,000 from the portfolio and an average amount of Rs.25,000 of Satyam. This is 3.5 times the pre-treatment average of Rs.8,277 and 4.8 times the pre-treatment average of Rs.5,152 for the net traded value and Satyam traded value respectively. This is also a little over than 20 percentage points when measured as a proportion of portfolio value.

The results indicate that the greater the exposure to the fraud, the greater is the withdrawal from the "bad stock". The results are consistent with (Odean, 1998) who finds that retail investors tend to sell entire positions than re-balance part of the position into another security.

5.3 By proximity to crisis location

It is often argued that proximity to the event matters in determining the response to an event. For example, Giannetti and Wang (2016) find that households located in the state in which a corporate governance scandal broke out, had a more negative response to stock market participation. Similarly, Gurun, Stoffman, and Yonker (2015) find that residents of communities that were more exposed to the Madoff fraud in the US subsequently withdrew assets from investment advisers.

In India, Satyam was the pride of the state of Andhra Pradesh (AP), both because the promoter ethnically belonged to the state of Andhra Pradesh, and because Satyam was headquartered in the state. In India, the top management of firms is often ethnically similar to that of the promoter. Investors in AP, even if they had not invested in Satyam themselves, may have been more aware of the fraud and felt its effects more directly than those outside of AP.

I narrow our attention to only the control investors, that is those, who did not own any Satyam stock one day prior to the crisis. I then conduct a DID on residents in AP vis-a-vis residents outside of AP. This also allows me to evaluate if there was indeed a sharp effect on trust, as the investors in this estimation do not own Satyam and could not have seen a loss in portfolio value owing to Satyam.

Table 9 Trading by non Satyam investors in AP

This table presents results from a DID regression where residents in AP are the treated group while residents outside of AP are the control group. Column (1) presents the results on net traded value, while Column (2) presents the results on net traded value as a percentage of portfolio value.

	NTV (Rs.)	NTV/Val (%)
	(1)	(2)
AP	−617.262***	0.5
	(137.89)	(1.6)
Post	−7,429.318***	−2.8***
	(66.21)	(1.0)
AP*Post	1,141.522***	−4.4
	(284.89)	(4.2)
Constant	2983.950***	−0.8
	(38.99)	(0.9)
Observations	524,477	524,477
Note:	*p<0.1; **p<0.05; ***p<0.01	

Column (1) in Table 9 presents the results on net traded value, while Column (2) presents the results on net traded value as a percentage of portfolio value. I find that, contrary to international literature, investors in AP *increase* their participation in the market. The coefficient on net traded value is Rs.1,142, which is 0.38 times the pre-treatment average of Rs.2,957. When estimated as a proportion of portfolio value, however, there is no difference between the trading of investors inside and outside AP.

Thus, I find no difference in the trading behaviour of those not exposed to Satyam in and outside of AP, and if anything, there was actually *cashing-in* of a small amount.

5.4 By investor experience

Prior experience of fraud as this is likely to have a high influence on risk preferences and expectations (Malmendier and Nagel, 2016). In India, the last scandal that matched the Satyam scandal was the Ketan Parekh scam. This scam that hit the stock market on March 1, 2001 led a 176 point crash on the BSE Sensex.[13] The scam had an especially high impact on the ten stocks, known as the K10 stocks held by Ketan Parekh.[14] The value of these stocks began to surge between January and July 1999, that led brokers and investors to also buy these stocks. The fraud unraveled after the crash in NASDAQ began to have an effect on the liquidity of these stocks in the Indian market, and it became

[13] The Budget was released the prior day, and had led to a 177 point surge in the Sensex.

[14] These include Aftek Infosys, Silverline, SSI, DSQ Software, Satyam, Mukta Arts, HFCL, Global Telesystems (Global), Zee Telefilms, PentaMedia Graphics and Padmini T.

difficult for him to make payments on many stocks, which led to a crisis.[15]

I would have liked to isolate those investors who had held one of these ten stocks in 2001 and study their response to the Satyam scandal. However, I only have detailed holdings data from 2003 onward. I, therefore, use the age of the investor, measured by the account opening date, as a proxy for prior experience of fraud. I divide investors into three groups: those with less than five years in the market (26,370 investors), those between 5-10 years in the market (13,688 investors), and those greater than 10 years in the market (403 investors). The latter group will have been through the KP scandal. Each treated investor in the three groups is paired with its control investor from the matching estimation. This ensures that I continue to compare investors that are alike in terms of their broad trading and portfolio characteristics.

Table 10 Trading by investor age

This table presents the results of the DID regressions on net traded value as a proportion of portfolio value. Column (1) presents the results of the less than five years in the market group, Column (2) of those between 5-10 years in the market, and Column (3) of those greater than 10 years in the market.

	Age of the investor (years in market)		
	less than 5	between 5-10	greater than 10
	(1)	(2)	(3)
Net traded value/ portfolio value			
Treat*Post	−13.2***	−6.5***	−3.2***
	(2.4)	(1.1)	(0.6)
State FE	Yes	Yes	Yes
Observations	577,143	320,779	9,123
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10 presents the results of the DID regressions. Column (1) presents the results of the less than five years in the market group, Column (2) of those between 5-10 years in the market, and Column (3) of those greater than 10 years in the market. I find that all the treated groups cashed out relative to the control group within seven days of the event. As a proportion of portfolio value, the magnitude of β_3 here is the largest for the youngest group (Column (1)). This is not surprising as if experience matters, then those relatively new to the markets are more likely to react by cashing out than those who have been in the market for longer.

[15]Ketan Parekh was arrested on 30th March, 2001. This led to another Sensex fall of 147 points.

5.5 By institutions

I have data on 1,026 institutions who held Satyam shares as of 6 January, 2009, one day before the crisis. I match these institutions on the same characteristics as described in the matching of individuals (Section 3.2). This gives me a matched set of "control" institutions.

I find that the treated institutions had a gross traded value of Rs.231 million over the seven days post the crisis, relative to a traded value of Rs.155 million by the control group. Thus, overall trading by the treated institutions was higher than control institutions, similar to the story on retail investors.

The average net traded value by the treated institutions was -Rs.59 million, relative to a pre-crisis traded value of 16.8 million. Similarly, average net traded value by the control institutions was -Rs.20 million post crisis relative to Rs.2 million pre-crisis. Treated institutions reacted more sharply than control institutions.

Table 11 Trading by institutions

	NTV (Rs.)	NTV/portval (%)
	(1)	(2)
Treat	−5,741.101	1.3***
	(6,107.539)	(0.004)
Post	−16,712.660***	0.1
	(2,231.116)	(0.035)
Treat*Post	−13,361.530	−5.7
	(8,158.044)	(0.102)
Constant	6,549.826***	1.8***
	(539.053)	(0.002)
Observations		
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 11 presents the results of the DID regression. The coefficient of β_3 on net traded value, the cashing out differential between treated and control institutions before and after the crisis, is Rs.−13,361. As a proportion of portfolio value, this is a "cashing-out" of 5.7 percentage points relative to the control group. Importantly neither of the two coefficients are statistically significant. This suggests that there was no differential response between the treated and control institutions after the Satyam crisis.

6 Threats to validity

A possible criticism of the analysis could be that there are unobservable differences between the treated and control group that are driving the behaviour. While the matching strategy controls for differences on observables, it does not account for differences such as risk aversion that are not captured by the variables available for analysis. Another criticism could be that when there is a portfolio loss, people always sell, and this has nothing to do with the impact of fraud revelation on trust. In this section, I address both these concerns.

6.1 The Maytas event

One way to test for unobservables is to look at people who once held Satyam, but for some reason did not on the day of the crisis. These investors are likely to be more similar to the treated investors, than those who have never purchased Satyam.

However, this differentiation is not entirely straightforward because of events like Maytas, and the resignation of independent directors that unfolded over the month of December 2008. Even though the scale of the accounting fraud at Satyam was entirely unexpected, it is possible that some investors exited around the time of the Maytas event (See Figure 6). It is possible that those who exited Satyam at the time (and therefore form part of the control group) "knew" something and contaminate the results.

I therefore divide our control group into three kinds: those that never held Satyam (strict control), those that exited Satyam before Maytas and those that exited Satyam after Maytas.

The second group allows me to test for importance of unobservables as these are the investors "similar" to the Satyam investors. The control group in this case (of those who exited before Maytas) consists of 6,373 investors. In the case of the latter, i.e. those who exited Satyam after Maytas, the control group consists only of 231 investors. This also underscores our contention that despite the Maytas event, the Satyam fraud was unexpected.

Table 12 presents the results. Column(1) is the main regression result (from Table 3). Column (2) uses only those observations as controls who have never had Satyam. Column (3) uses those observations who gave up Satyam before the Maytas scandal, that is they once held Satyam and had sold out before even the Maytas scandal broke out. Column

Figure 6 Net traded value over two weeks pre and post the crisis

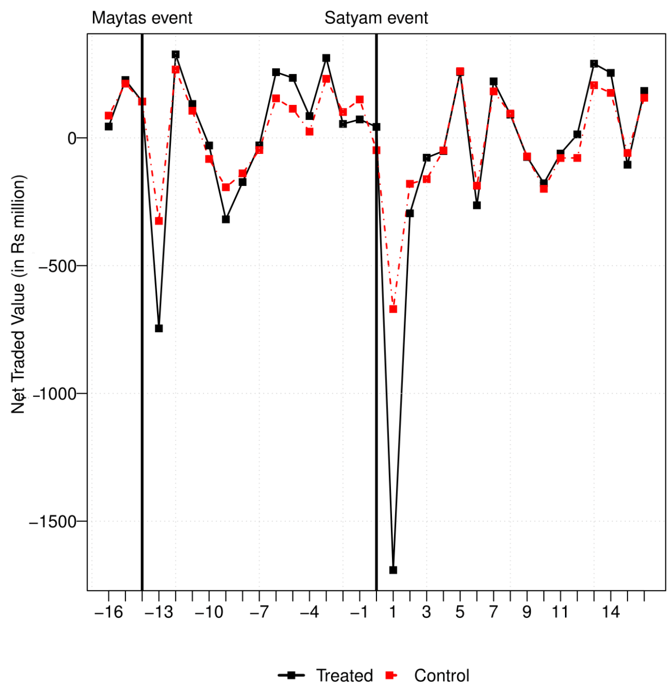
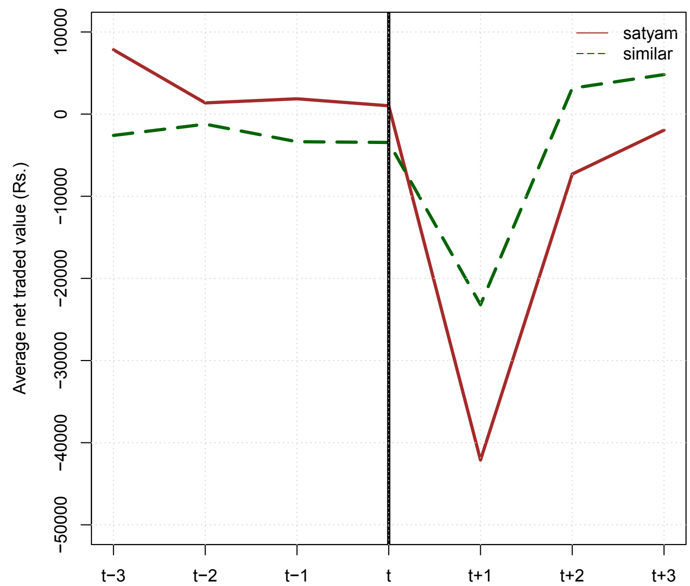


Table 12 Restricting estimation to different control groups

	Full sample (1)	Strict Control (2)	Gave up before Maytas (3)	Gave up after Maytas (4)
NTV/portfolio value				
Treat*Post	−10.7***	−9.5***	−13.8***	−14.3
	(1.6)	(1.4)	(3.7)	(16.8)
Observations	1,049,093	1,012,500	539,623	37,252
State FE	Yes	Yes	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01	

Figure 7 Net traded value on Satyam and similar loss days



(4) uses those investors as controls who gave up after Maytas.

I find that Satyam investors cashed-out more than non-Satyam investors, except in the case of those who had exited Satyam after Maytas. When this group is used as the control group, there is no statistically significant difference in cashing out. It is possible that those who got out at the time of Maytas continued to be affected by Satyam events. However, given the magnitude of the coefficient which is similar in size to the other coefficients, I think that the non-significance is driven by the small sample size (only 231 control investors) as is evident in the large standard errors.[16]

6.2 Nothing Satyam about it

The Satyam crash directly hit the portfolio of those who held Satyam on that date. One could argue that when such a portfolio loss occurs, investors always cash out, and there is nothing special about the Satyam event. I therefore evaluate the cashing out behaviour of the treated households at some point in the past, when their portfolio took a hit, similar to that on the Satyam date.

[16] A simple t-test on the differences in means on net traded volume post the event reveals a t-stat of 5.48, which is significant at the 1% level.

For each treated investor, I calculate the portfolio loss to the Satyam investor in the event of the crash. I then find a date on which the same investor faced a similar loss. I then plot the average net traded value for a seven day window on both these dates. Figure 7 shows the results. I find that on the similar portfolio loss dates, there is a sharp fall in the net traded value i.e. investors cash out. However, the magnitude of the fall is lower than the Satyam case. This suggests that the effect we see is specific to the "Satyam" event.

7 Conclusion

In this paper I study the impact on investor behaviour of fraud revelation. I ask if investors with direct exposure to stock market fraud are more likely to decrease their participation in the stock market than investors with no direct exposure to fraud, over both the short and long run? I use daily holding data from the National Stock Depository Limited (NSDL), the largest depository in India, and a matching methodology to compare investors directly exposed to fraud with investors who were not directly affected.

I find that investors with direct exposure to Satyam trade more intensely immediately i.e. over seven days after the Satyam event relative to control investors, and that this trading was largely driven by *cashing out* of the portfolio. Treated investors cash out almost 10.6 percentage points more of their overall portfolio relative to control investors post the crisis. The cashing out is largely restricted to the "bad stock". If anything, treated investors make *net purchases* of related stocks during the same period. Over the period of a month, there is no difference in the trading behaviour of the treated and control investors.

This paper, for the first time, is able to capture trading behaviour on a daily basis for an extended period of time instead of basing the analysis on household survey data, or observing investors at monthly or yearly frequency. It is also the first to focus on the impact of fraud in an emerging market, which is characterised by low participation, low financial literacy, and a larger trust deficit.[17]

The results raise questions on the importance of cultural and institutional settings on investor behaviour. For example, household survey data from India indicates portfolios of Indian households, are dominated by real assets such as gold and real estate, and barely 2 percent of the country participates in the stock market (Badarinza, Balasubramaniam,

[17]The World Values Survey evidence shows that low income countries have lower levels of trust capital.

and Ramadorai, 2016). Within the class of investors that do participate in the stock market, it is believed (anecdotally) that retail participants are largely dominated by "day traders". And while India does well on corporate governance metrics on the World Bank ease-of-doing business indicators, on the ground there is general skepticism about corporate governance standards.

It is in this context of limited stock market participation, and high mistrust of accounting standards that the Satyam fraud needs to be placed. In such a setting, it is possible that an accounting fraud, even as big as Satyam, does not damage trust perceptions of those already in the market relative to mature market settings with higher participation rates and higher expectations of governance standards. It is also possible that swift government action, as was taken after Satyam (Vikraman, 2016), has a larger pacifying effect in such economies than in more mature economies. Of course, instances of fraud may deter participation on the extensive margin, and cause fewer people to enter the market, but data restrictions prohibit us from throwing light on this important question.

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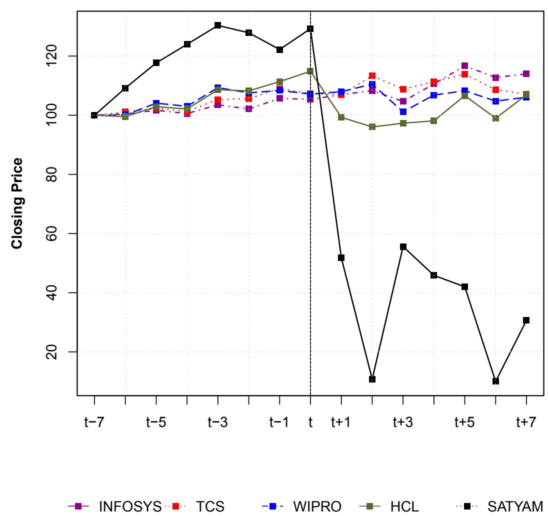
Appendix

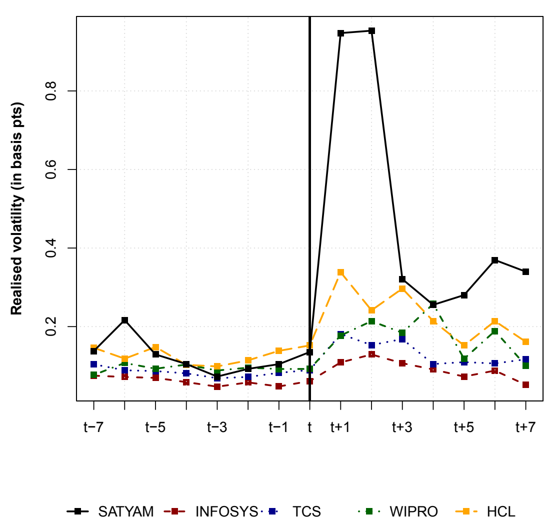
A Timeline of events

	Event	Date
1	Satyam announces $1.6bn acquisition of Matyas Infra and Maytas properties	2008-12-16
2	Citigroup, JP Morgan and Merrill Lynch downgrade Satyam and slash their share price estimates by up to half.	2008-12-17
3	World Bank bars Satyam from doing business with it directly	2008-12-23
4	First independent director resigns from Satyam board	2008-12-24
6	Satyam appoints Merrill Lynch to review strategic options to enhance shareholder value	2008-12-27
7	Three more independent directors quit Satyam board	2008-12-29
8	London-based World Council for Corporate Governance, which awarded Satyam a Golden Peacock last year, said it was seeking legal advice to understand the mechanics of the aborted takeovers as part of its effort to re-assess whether Satyam still deserved the award.	2009-01-05
9	Mr.Raju admits to falsifying Satyam books, and resigns	2009-01-07
10	Chief financial officer (CFO) Vadlamani Srinivas resigns	2009-01-08
11	Mr. Raju is arrested	2009-01-09
12	Finance head Srinivas arrested	2009-01-10
13	Central Govt. reconstitutes satyam board	2009-01-11
14	Deloitte, KPMG named new joint auditors. Satyams former auditor, PricewaterhouseCoopers (PwC), says its opinion on the IT firms financials may be rendered inaccurate and unreliable	2009-01-14
15	Govt. orders probe into the scandal	2009-01-19
16	Mr. Raju confesses to diverting funds to Maytas	2009-01-21
17	Former Satyam auditor PWCs S. Gopalakrishnan and Srinivas Talluri arrested	2009-01-24
18	The board appoints Goldman Sachs and Avendus, an Indian investment bank, to identify strategic investors	2009-01-27
19	Former Nasscom chairman Kiran Karnik appointed Satyam chairman	2009-02-06
20	Govt. appointed board meeting deciding strategic investors	2009-02-21
21	Satyam gets permission to sell 51% majority stake from SEBI	2009-03-06
22	Tech Mahindra selected as strategic investor	2009-04-13

B Comparing Satyam with its competitors

This figure shows a comparison of Satyam with that of its main competitors. The top panel the daily close price, obtained from the NSE. The bottom panel shows the realised volatility. This is computed using intraday day returns of a stock at NSE aggregated at 12 second frequency. We split the entire day's trading time is split into 5 minute windows and compute the standard deviation of returns of the stock in all windows. The mean of all the standard deviation values is considered the daily realised volatility of the stock.





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