Stock market participation in the aftermath of an accounting scandal

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Abstract

In this paper we study the impact on investor behaviour of fraud revelation. We 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? We use daily holding data from the National Stock Depository Limited (NSDL), and a matching methodology to compare investors directly exposed to fraud with investors who were not directly affected. We find that investors with direct exposure trade more intensely over seven days after the event relative to control investors, and that this trading is largely driven by cashing out of their portfolio. Within a month, however, treated investors cash-in into their portfolios. The impact on under-diversification is more persistent.

*We thank Susan Thomas at the Finance Research Group, IGIDR for access to data, and for useful discussions. We thank Anurag Dutt for excellent research assistance. We thank NSE-NYU initiative on financial markets for funding support. All errors are our own. PRELIMINARY DRAFT. PLEASE DO NOT CIRCULATE.

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1 Introduction

Research on investor participation in financial markets has produced certain evidence on investor irrationality 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). More recent work suggests that investors personal experiences play a disproportionate role in shaping their risk appetite and consequently their trading decisions (Malmendier and Nagel, 2011; Malmendier and Nagel, 2016; Anagol, Balasubramaniam, and Ramadorai, 2015).

A related question is how do investors react to major shocks in the market? Dorn and Weber (2013) and Hoffmann, Post, and Pennings (2013) focus on individual trading in times of financial crisis, and find that a crisis significantly affects risk perceptions, and consequently trading behaviour. The shock studied here is an aggregate shock to the entire market, and not to specific stocks. Giannetti and Wang (2016) find evidence based on US data that instances of fraud revelation lowers household participation in stock markets by lowering trust.

In this paper we use a remarkable natural experiment to obtain new evidence about these questions. We ask, how do investors behave when revelation of fraud is likely to have lowered trust, and caused panic in minds of investors? As recent literature suggests, personally experienced outcomes are over-weighted compared to rational Bayesian learning (Kaustia and Knupfer, 2008; Malmendier and Nagel, 2016) We, therefore, 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? More importantly, we ask if the reaction to fraud is an immediate response or continues to persist over long horizons?

We narrow our 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. This news was a complete surprise, and had the market shaken.

Our data on daily holdings comes from the National Securities Depository Limited (NSDL), the largest depository in India in terms of total assets tracked (roughly 80%). We are thus able to capture trading behaviour immediately after the event, and on a daily basis for an extended period of time. We focus on investors who held Satyam shares in their accounts one day prior to 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.

We 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 de-investing. Those with larger exposure to Satyam in their portfolio sell more than those with lower exposure. We find that de-investment effect of 36% relative to the pre-treatment average. Over the period of a month, however, the magnitude of the difference falls. If anything, treated investors are seen to make net purchases into their portfolio. Our results are therefore contrary to early work which shows huge withdrawals from the market. The effect of fraud on investor trading seems to be short-lived.

We are able to add to the current state of knowledge because of three reasons. First, unlike papers that look at the financial crisis as a whole, we are able to isolate a single instance of fraud that largely affected only that stock, and not the entire market. Second, unlike papers that base their analysis on household survey data, or observe investors at monthly or yearly frequency, we observe daily data of investors at the individual account level, which allows us to differentiate between immediate vs. more long term impact of the shock.

Finally, our paper is 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.[1] The literature on limited participation in emerging economies, especially India, has so far focused 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). According to the evidence so far, low trust is a consequence of sharp sales practices, and not of failure of regulation on corporate governance of financial market entities themselves. The channel of trust is also suggestive, that is, there is no direct evidence that can help link fall in trust to investor decisions. This paper is able to contribute towards this question.

The paper proceeds as follows. Section 2 describes the research setting. Section 3 explains the research design. In Section 4 we describe the data, and in Section 5 we discuss the results. Section 6 describes the robustness checks. Section 7 concludes.

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

2 The research setting

Low participation of households in stock markets is a feature of several developed countries (Guiso and Sodini, 2013), and is particularly salient in an emerging economy such as India. For example, while gross savings in India were about 30 percent of GDP in 2013-14, net financial saving of households was only 7.1 percent.[2] Household survey data indicates that at the median Indian households hold Rs.2000 (US$30) in financial assets, and Rs.20,000 (US$300) in gold. Portfolios of Indian households, are thus dominated by real assets such as gold and real estate (Badarinza, Balasubramaniam, and Ramadorai, 2016). It is in this context of limited stock market participation that the Satyam fraud needs to be placed. We now turn to describing the event in more detail.

2.1 The accounting fraud at Satyam

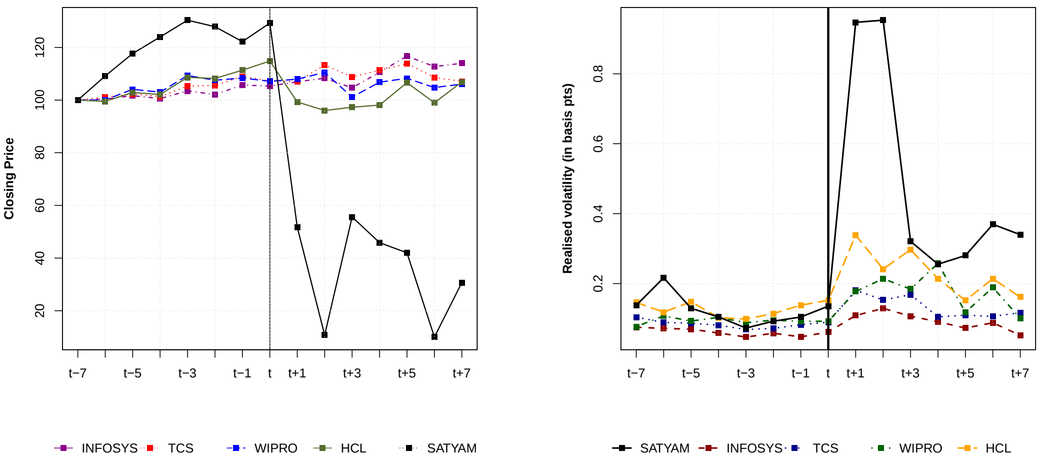
When India emerged out of its license raj, into a post-liberalised era in the early the 1990s, the software revolution played an important role in integrating India to globalisation. Satyam, based in Hyderabad, the capital of the then state of Andhra Pradesh[3] was an IT company of that time and offered software development, system maintenance, packaged software 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). An investigation was launched by the government into the scam, and the main promoter of the firm was arrested. Investors in Satyam are said to have lost almost Rs.136 billion (US$2 billion) over the next month. However, the announcement was a total surprise, and 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 (Wharton, 2009).

We confirm this by Figure 1 which compares Satyam with its top competitors in the IT sector, and Figure 2 which shows a comparison of Satyam as against the NSE-Nifty market index. The left panel in each graph shows the daily close price, obtained from

[2]Table II.1: Gross Saving (As a ratio of GNDI), Annual Report, RBI, 2013-2014.
[3]The state has recently split into Telangana and Andhra Pradesh

Figure 1 Close price and realised volatility of IT companies



the NSE. The right hand panel shows the realised volatility. [4] 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. After the announcement, while Satyam did take a beating, similar falls were not experienced by any other stocks.

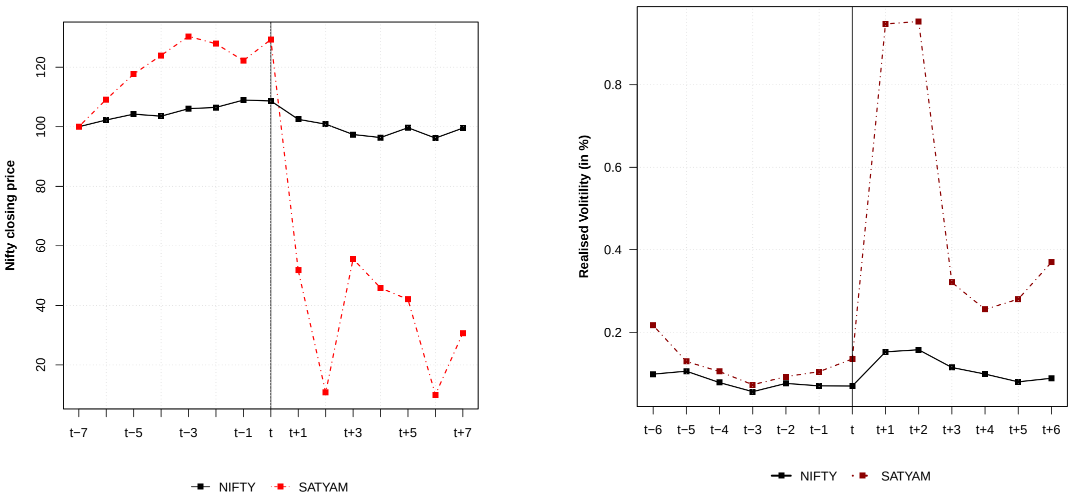
The disaster was mostly a result of an accounting fraud and is said to have had serious ramifications on investor confidence. This allows us to use the Satyam event to study the impact on investor participation of a revelation of a large-scale fraud.

3 Research design

In the event of a large unexpected exogenous loss as a result of the Satyam fraud, what would we expect of investors in the short-term and beyond?

[4] 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.

Figure 2 Close price and realised volatility of Nifty



We 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 lower their inclination to participate in the equity market. There are three kinds of withdrawals that are possible:

1. *Withdrawal in terms of selling existing stock on the market.*

   Previous literature suggests that investors personal experiences play a disproportionate role in shaping their risk appetite and consequently their trading decisions (Malmendier and Nagel, 2011; Malmendier and Nagel, 2016; Anagol, Balasubramaniam, and Ramadorai, 2015). This suggests that those who were "exposed" to Satyam would show a larger effect.

2. *Withdrawal from particular "bad" sectors*

   Research suggests 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 (Griffin and Tversky, 1992). Investors should therefore extrapolate to the market as a whole, and more specifically to stocks similar to Satyam, such as other IT stocks.

3. *Withdrawal over the long term*

   Guiso, Sapienza, and Zingales (2008) argue that low trust is a detriment to stock market participation. Giannetti and Wang (2016) find evidence based on US data that fraud revelation lowers household participation in stock markets by lowering trust. A stock market scandal such as the Satyam fraud should permanently dent investors and lower their participation on the market over the long term.

In this paper we focus on measuring the first two kinds of "withdrawals" from the market. We want to evaluate if investors exit the particular stock, or trade less on the market overall after the scandal. We also want to evaluate if investors end up with more under-diversified portfolios as a result.

3.1 Outcomes of interest

Participation on the intensive margin can be measured using the difference in the daily holdings data of each investor. Giannetti and Wang (2016) use the change in household's holding of a particular stock between two time periods to measure the participation. We use a similar measure to calculate the *total traded value* between two days. This is calculated as follows:

$$tv^i_{t+1} = \sum_k abs(p^k_t h^{ik}_{t+1} - p^k_t h^{ik}_t)$$

tv is the absolute value of the total traded value of shares by investor i at time $t+1$, h is the quantity of shares of stock k held by person i, and p is price of stock k. This accounts for both, portfolio rebalancing by a person, as well as the purchase that was made using new money and sales that was not reinvested in the market.

We calculate *net traded value* which is the difference between the total buy trades and total sell trades between $t+1$ and t. This captures the *net purchase* element of investor trades, and is a more appropriate measure of the investment (or de-investment) of the investors portfolio. For example, if an investor bought Rs.100 worth of shares, by selling Rs.100 worth of existing shares, then the net traded value in this case would be 0, as there would be no new money coming in, or money being taken out. 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.

We measure the portfolio quality of the investor by calculating the extent of under-diversification of the portfolio, as well as the beta of the portfolio. These are calculated using a market model with the value-weighted universe of Indian stocks as the market portfolio.

3.2 The need for matching

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). We therefore require the unraveling of a fraud that was not unearthed because of a down-turn. Another problem in identification is that the outcomes are not an effect of fraud, but a result of unobserved preferences of investors.

To test the hypothesis we 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 we 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, we use the he 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:

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

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.

Our focus is the impact of fraud on investor behaviour. It is, therefore, important to control for similarities in investor characteristics. Since we do not have access to demographic details of the investors, we focus our attention on details related to investment behaviour, that is accessible using holding data of the accounts prior to the Satyam event. The observables for our 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. We therefore measure if an investor had traded at least once 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. We 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. We therefore match our investors on log of the portfolio value measured as of the 6th September, 2009.

3.3 Difference-in-difference

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

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

where $Y_{i,t}$ is the traded value as a proportion of portfolio value, or the net traded vale 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 trading (and negative an 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.

4 Data

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

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

In our data-set a single investor can hold multiple accounts. However, we are able to merge all accounts with a single Permanent Account Number (PAN) number[5], to arrive at an estimate of one account per investor.Permanent Account Number. We 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.

Figure 3 shows the number of investors with Satyam holdings as a proportion of total number of investors in each state across the NSDL sample, as of 6 January, 2009. We then plot the distribution of the percentage of Satyam account holders in five buckets. Here the 20th percentile value corresponds to 0.66% i.e. districts which have less than equal to 1.35% of total accounts with Satyam stock. The 40th percentile value corresponds to 1.11% of total accounts, the 60th percentile value to 1.85% and the 80% percentile value - 3.15% of total accounts. The maximum value of a district is 14.28%. Thus, we find that the districts in states of Gujarat, Maharashtra, Karnataka, Andhra Pradesh (and now Telangana) and Tamil Nadu have about 3% or more accounts which held Satyam stocks as of the date of the crisis.[6]

[5]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.

[6]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 head quarters of Satyam in Hyderabad

Figure 3 Satyam holdings as of 6 January 2009

This figure shows the number of investors with Satyam holdings as a proportion of total number of investors in each district across the NSDL sample, as of 6 January, 2009. We then plot the distribution of the percentage of Satyam account holders in five buckets. Here the 20th percentile value corresponds to 0.66% i.e. districts which have less than equal to 1.35% of total accounts with Satyam stock. The 40th percentile value corresponds to 1.11% of total accounts, the 60th percentile value to 1.85% and the 80% percentile value - 3.15% of total accounts.

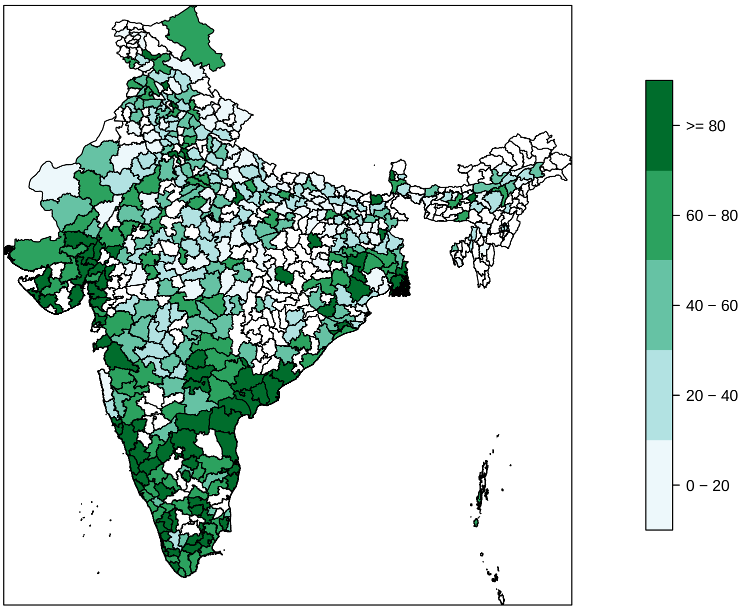
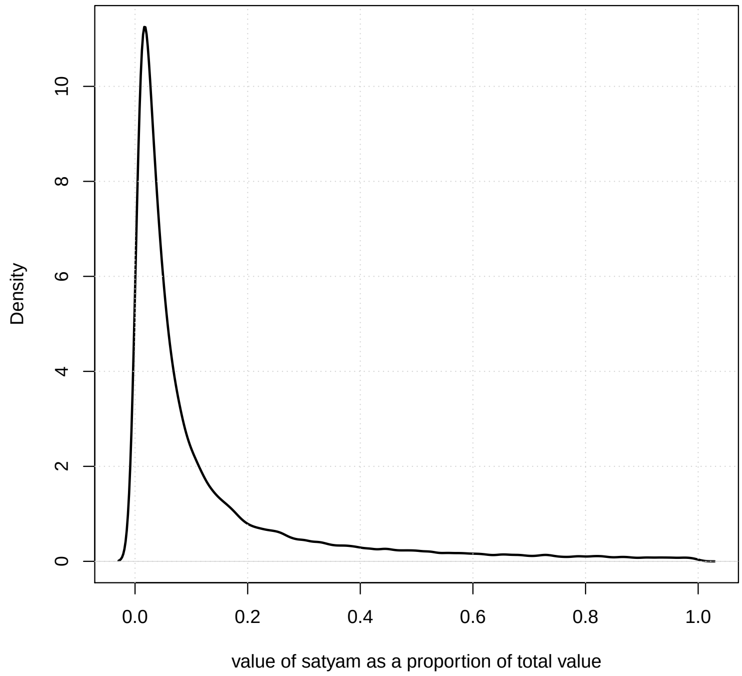


Figure 4 Satyam value as a proportion of portfolio value as of 6 January 2009

This figure shows the value of Satyam shares as a proportion of total portfolio value as of 6 January, 2009.



4.1 Sample

We focus our attention on analysis of a stratified random sample of investors from the NSDL universe. The sample is created as follows. We 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. We 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.

We then remove observations whose portfolio value as of 6 January, 2009 is greater than a Rs.1 million. This gives us a sample of 423,362 investors. Of these, 10% or 40,461 investors held Satyam shares prior to the crisis date. Figure 4 plots the value of Satyam shares of the Satyam owners as a proportion of total portfolio value just prior to the crisis. The mode of the distribution was 0.28. The mean was 0.2, while the median was 0.07.

Table 1 shows the summary statistics of Satyam and non-Satyam holders. Satyam holders are a little older than non-Satyam holders – the average number of years they have been

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

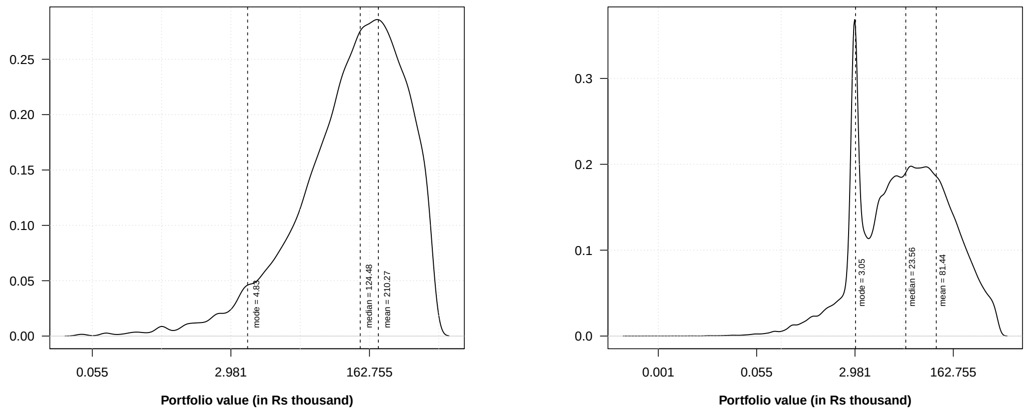
*** indicates statistically significant at 1% level

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. This suggests that the Satyam group is likely to be more under-diversified.

Figure 5 shows the density plot of log portfolio values of both the treated and control group one day prior to the announcement. The left panel shows the density plot for the Satyam holders, while the right panel shows the density plot for the non-Satyam holders. Consistent with what we see in Table 1, we find the while the mode of the two distributions are relatively similar, there is a huge difference in the mean. This suggests that a smaller proportion of Satyam holders are wealthier (in terms of equity assets), and skew the distribution towards the right. This, and other differences discussed earlier underscore the need for a matching framework.

Figure 5 Portfolio value

The graph shows the density plot of log (portfolio value) of treated investors (i.e. those who held Satyam shares) in the left panel, and control investors (matched) in the right panel. The y-axis however, represents a normal scale, and not a log-scale.



4.2 Do we have match balance?

The matching methodology described in Section 3 provides us with 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).

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). We therefore need to verify that this balancing condition is satisfied by the data.

We first present results from parametric tests for matching in Table 2. These include the coefficients out of a paired t-test and standardised bias 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. We also report the KS-test statistic.

Column (5) in Table 2 shows the t-statistic and column (7) reports the standardized difference, Column (8) reports the KS-statistic. The t-stats confirm that there is no significant difference in means between the two groups, while the KS-statistic shows that

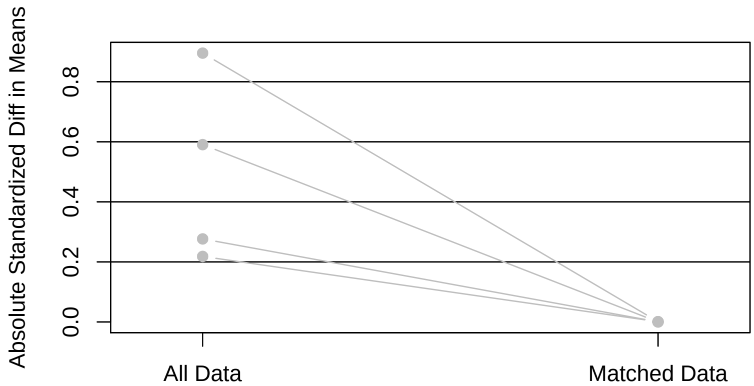
Table 2 Match balance: t-stat, standardised difference and ks-stat

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	-0.12	0.90	-0.08	0.02	0.00**
Log (portfolio value)	11.46	10.06	1.75	1.39	0.12	0.00	0.084	0.004	0.90
Had traded	0.42	0.13	0.34	0.29	0.00	1	0	0	1
Account age	4.46	3.67	2.53	0.79	-0.05	0.95	-0.037	0.006	0.52

Figure 6 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.



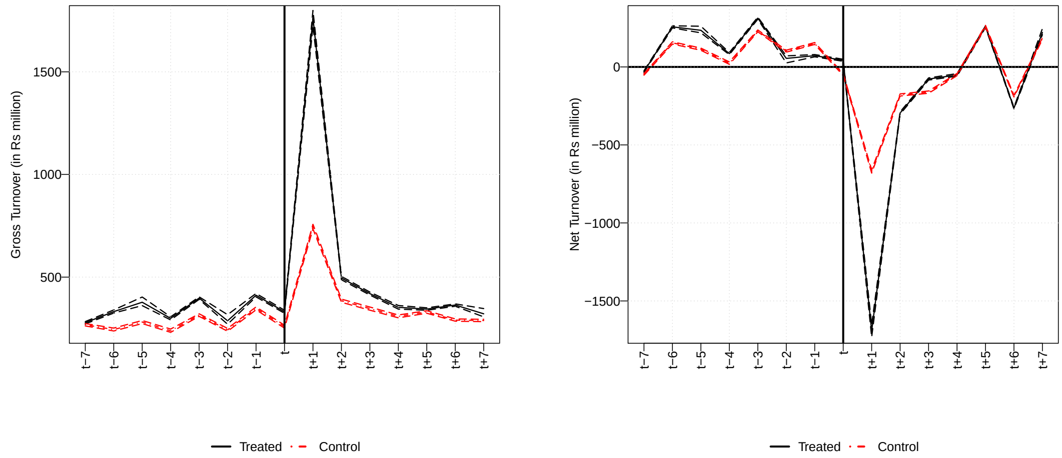
there is no significant difference in the distributions between the two groups (except for the portfolio beta variable). The lower the standardised difference, the more balanced the treatment and control groups are for the variable in question. While there is no formal criterion for appropriate value of standardized difference, a value of upto 20 is considered acceptable (Rosenbaum and Rubin, 1985).

We also present the change in the standardised bias for all the covariates after matching in Figure 6. The standardised bias has fallen dramatically after matching, and we take this as evidence for the existence of a reasonable matched control sample.

The t-test also does not show a significant difference for all variables, including those for whom the KS-statistic is statistically significant leading us to believe that the balancing conditions are satisfied for each variable.

Figure 7 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) five days before and after the Satyam crisis announcement. The vertical bar marks the date prior to the fraud revelation date.



5 Results

We analyse for the causal impact of the Satyam crisis on investor participation in stock markets. We first present graphical evidence on total value traded, and net value traded around the date of announcement, and then present the results of a DID regression.

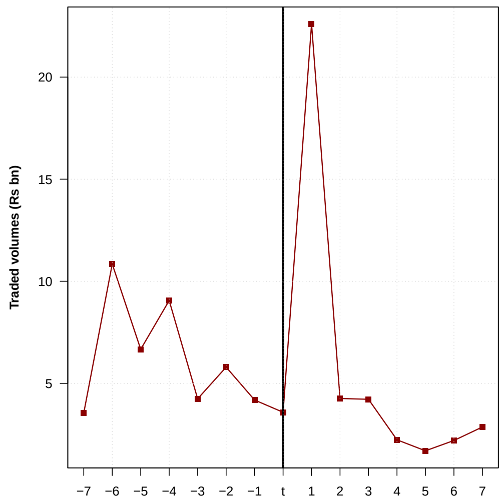
5.1 Overall trading in the market

Figure 7 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. We 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.

The graph shows that over the seven days after the Satyam announcement, the total traded value of treated investors increased. At the same time, the total traded value in-

Figure 8 Total traded volumes (Rs.billion)

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



creased, but by a much smaller amount, for the matched, non-Satyam investors. Overall, the treated group had a gross traded value of Rs.3.7 billion, while the control group had Rs.2.4 billion over the seven day period.

The right panel of the figure indicates that the sale of stocks constituted a large part of the trading volumes. Treated investors (i.e. those who held Satyam stock) were greatly impacted, and sold out their equity holdings on the date of the announcement. The overall net traded value of treated investors over this period was -Rs.2.1 billion, while that of control investors was -Rs.0.9 billion.

We ask if the net sales by the treated investors were driven by Satyam shares. Figure 8 shows the total traded volumes on NSE of Satyam. Traded volumes saw a sharp rise one day after the scandal, and subsided after. When we look at the entire treated group, we find that the total traded value of Satyam in the 7 days was Rs.1.4 billion, while that of the control group was Rs.46 million. Thus, almost 37% of traded value of the treated group was from Satyam trades, while the corresponding number for the control group was 2%.

The net traded value i.e. the amount of Satyam de-invested by treated investors over the 7 days was Rs.-1.1 billion. This is almost 57% of the net traded value, suggesting that a large proportion of the exit by Satyam investors was of the Satyam stock. The control investors actually had a positive net traded value i.e. they “bought” Satyam shares after the scandal worth Rs.22 million. This suggests that the effect of Satyam was large and negative on the trading behaviour of the treated group as a whole. The control group, on the contrary, seems to have seen this as an opportunity to buy some of the depressed stock.

5.2 Do investors de-invest?

If treated investors as a whole de-invested, what is the average amount of de-investment by such investors? How has this changed after the scandal? The DID regression estimates on net traded value (in Rs.) and net traded value as 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. We are interested in the coefficient (β_3) on the Treat*Post interaction term. This gives us the difference between the amount de-invested by treated and control group before and after the event.

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 results presented are from a robust regression.

	Dependent variable:	
	NTV (Rs.)	NTV/Val (%)
	(1)	(2)
Treat	610.053***	0.5***
	(15.164)	(0.01)
Post	−4,431.651***	−3.9***
	(14.158)	(0.01)
Treat*Post	−1,386.274***	−1.2***
	(20.018)	(0.01)
Constant	1,897.839***	1.4***
	(21.436)	(0.01)
State FE	YES	YES
Observations	1,048,090	1,048,090
Residual Std. Error (df = 1048067)	3,933.966	0.027
Note:	*p<0.1; **p<0.05; ***p<0.01	

The results indicate that a large proportion of the trades of the treated group were sales of stocks, consistent with Figure 7, shown earlier. The β_3 coefficient shows that the amount de-invested was about -Rs.1,386.27. This is a de-investment of 36% relative to the pre-event average of Rs.3802. Treated investors de-invested about 1.2% as a proportion of total portfolio value. The Satyam crisis had a statistically significant impact on investors who held Satyam stock. When investors heard bad news, their immediate response was to sell shares on the market.

5.3 Does de-investing vary with exposure to Satyam?

In the class of investors that held Satyam, it is likely that the high trading is driven by those whose Satyam holdings were a large part of the portfolio. These investors would have seen sharp drops in their portfolio values as the Satyam saga unfolded, and we expect that greater withdrawals will be seen by those with greater Satyam exposure.

We divide the treated investors into quintiles based on the value of Satyam in their portfolio as a proportion of portfolio value, one day prior to the event. We then find their partners from the matching exercise, and conduct a DID on net traded value for each. Table 4 shows the results on trading over 10 days of pre and post data.

We find that all the treated investor groups traded more than their respective control groups. However, the magnitude of the difference increases by portfolio exposure. Investors with the largest exposure to Satyam in their portfolios (Column (5)) have a β_3 coefficient for the net traded value regression of negative Rs.1731, and a coefficient of 7.5%, for the net traded value as a proportion of portfolio value regression. These are large coefficients relative to the group with the lowest exposure to Satyam (Column (1)). This suggests that the greater the exposure to the fraud, the greater is the withdrawal from the market, in the short run.

5.4 Does de-investing vary with experience?

Prior experience of fraud 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 hit the stock market on March 1, 2001 led a 176 point crash on the BSE Sensex.[7] The stock had an especially high impact on the ten stocks, known as the K10 stocks held by Ketan Parekh.[8] 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 difficult for him to make payments on many stocks, which led to a crisis.[9]

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

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

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

Table 4 Trading by exposure to Satyam (over one week)

The table presents results from a DID regression on net traded value (NTV) in Panel 1 and NTV as a proportion of portfolio value in Panel 2 on 10 days of data pre and post the event. Columns (1) to (5) represent the quintiles of matched treated-control pairs by exposure to Satyam, with Column (1) representing the first quintile of exposure to Satyam, and Column (5) representing the fifth quintile of exposure to Satyam.

	Dependent variable:				
	NTV (Rs.)				
	(1)	(2)	(3)	(4)	(5)
Treat	379.127***	318.941***	315.925***	414.241***	848.972***
	(57.962)	(41.538)	(29.707)	(19.802)	(17.118)
Post	−9,892.477***	−6,764.210***	−4,503.453***	−2,564.918***	−1,251.839***
	(54.250)	(38.892)	(27.718)	(18.411)	(15.786)
Treat*Post	−939.107***	−705.770***	−627.435***	−738.079***	−1,730.751***
	(76.706)	(54.983)	(39.176)	(26.015)	(22.345)
Constant	4,063.893***	2,766.790***	1,860.467***	1,106.396***	556.658***
	(88.948)	(61.099)	(42.925)	(26.801)	(22.354)
Observations	210,229	210,238	210,091	209,757	207,775
Residual Std. Error	7,239.088	5,049.720	3,501.658	2,266.420	1,928.868

	Dependent variable:				
	NTV/val (%)				
	(1)	(2)	(3)	(4)	(5)
Treat	0.1***	0.1***	0.2***	0.5***	1.9***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
Post	−3.9***	−3.9***	−4.0***	−4.0***	−3.8***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Treat*Post	−0.2***	−0.2***	−0.4***	−1.1***	−7.5***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)
Constant	1.4***	1.4***	1.4***	1.5***	1.4***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
Observations	210,229	210,238	210,091	209,757	207,775
Residual Std. Error	0.022	0.022	0.024	0.028	0.044
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5 Impact by age (one week)

The table presents results from a DID regression on total traded value (TV) and net traded value (NTV) as a proportion of portfolio value on one week of data pre and post the event. Columns (1) to (3) represent the matched treated-control pairs by years of experience in the market.Column (1) represents those with less than 5 years of experience in the market, Column (2) those between 5 and 10 years, and Column (3) those with more than 10 years of experience.

	Dependent variable:		
	net_turnover		
	(1)	(2)	(3)
Treat	479.140***	954.580***	865.441***
	(14.926)	(36.768)	(248.451)
Post	−3,374.597***	−6,885.855***	−8,499.066***
	(13.876)	(34.501)	(242.903)
Treat*Post	−1,078.488***	−2,157.112***	−2,153.621***
	(19.618)	(48.793)	(343.279)
Constant	1,439.221***	2,931.930***	4,035.042***
	(20.574)	(54.422)	(481.134)
Observations	682,053	355,573	10,464
Residual Std. Error	3,058.664	5,849.449	7,071.504

	Dependent variable:		
	NT/val (%)		
	(1)	(2)	(3)
Treat	0.5***	0.4***	0.2**
	(0.01)	(0.02)	(0.1)
Post	−4.0***	−3.7***	−3.7***
	(0.01)	(0.01)	(0.1)
Treat*Post	−1.3***	−1.1***	−0.7***
	(0.02)	(0.02)	(0.1)
Constant	1.5***	1.4***	1.5***
	(0.02)	(0.02)	(0.2)
Observations	682,053	355,573	10,464
Residual Std. Error	0.029	0.025	0.024
Note:			*p<0.1; **p<0.05; ***p<0.01

We 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, we only have detailed holdings data from 2003 onward. We therefore, use the age of the investor, measured by the account opening date, as a proxy for prior experience of fraud. We divide investors into three groups: those with less than five years in the market, those between 5-10 years in the market, and those greater than 10 years in the market. 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 we continue to compare investors that are alike in terms of their broad trading and portfolio characteristics.

Table 5 presents the results from a DID regression on one week of data. Columns (1) to (3) represent the matched treated-control pairs by years of experience in the market.Column (1) represents those with less than 5 years of experience in the market, Column (2) those between 5 and 10 years, and Column (3) those with more than 10 years of experience. The top panel presents results on net traded value (in Rs.) while the bottom panel presents results on net traded value as a proportion of portfolio value.

We find that, consistent with the main result, trading of all groups was largely driven by investors de-investing from the market. From a rupee value perspective, the youngest group actually sees the least de-investing (with a coefficient of -1078), but as a proportion of portfolio value, the coefficient is the largest for the youngest group. If experience matters, then those relatively new to the markets are more likely to react by de-investing than those who have been in the market for longer.

5.5 Is de-investing largely about Satyam stock?

The Satyam scandal was an accounting scandal. It is possible that when the news broke out, investors felt that it was a losing proposition to hold on to Satyam shares, and rushed to sell them. Earlier research has focused on the financial crisis, where there is not one source of the problem (Dorn and Weber, 2013; Hoffmann, Post, and Pennings, 2013), or focused on household survey data, where it is difficult to isolate daily trading of the "scandal" stock (Giannetti and Wang, 2016).

We, therefore, narrow our attention to those who owned Satyam stock prior to the crisis. We know that the treated group offloaded their Satyam shares post the event. We test if the sale of Satyam shares was higher by exposure to Satyam.

In Table 6 we present the results on the trading on Satyam shares by exposure. The sample here is the treated group only. As shown in the Table, we find that those with

Table 6 Net traded value of Satyam stock

	Dependent variable:
	NTV Satyam (Rs.)
Post	−372.773***
	(5.806)
Exposure Q2:post	−265.923***
	(8.211)
Exposure Q3:post	−450.003***
	(8.211)
Exposure Q4:post	−682.936***
	(8.213)
Exposure Q5:post	−1,453.275***
	(8.234)
Constant	123.304***
	(5.605)
State FE	YES
Observations	524,616
Residual Std. Error	713.566 (df = 524597)
Note:	*p<0.1; **p<0.05; ***p<0.01

greater exposure to Satyam sell more of Satyam stock.

5.6 Does de-investing get carried over to other IT 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.

We are able to test if investors in our sample extrapolate the Satyam news to other IT stocks. We evaluate if the de-investment seen in the immediate few days after the crisis relate to other stocks in the IT sector.

The results are presented in Table 7. Column (1) presents the net traded value of other IT stocks, and Column (2) presents the net traded value of non-IT stocks. We find that the treated investors have de-invested, but by very small amount, in the IT stocks. They seem to have invested in other non-IT stocks.

While the effect on IT stocks is statistically significant, the effect does not seem economically significant. This suggests that investors exposed to a scandal did not necessarily

Table 7 IT and non-IT stocks

	Dependent variable:	
	NTV (IT stocks)	NTV (Non-IT stocks)
	(1)	(2)
Treat	3.106***	−27.771**
	(0.046)	(12.172)
Post	−4.317***	−4,017.202***
	(0.043)	(11.361)
Treat*Post	−3.914***	79.760***
	(0.060)	(16.065)
Constant	2.232***	1,702.591***
	(0.065)	(17.202)
State FE	YES	YES
Observations	1,048,876	1,048,876
Residual Std. Error (df = 1048853)	9.213	3,194.085
Note:		*p<0.1; **p<0.05; ***p<0.01

extrapolate to other similar stocks.

5.7 Does de-investing last over time?

A question that arises is if such excessive selling persisted after several days of the event. In Table 8, we 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 xxx 2008 to xxx 2009. 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.

Investors in Satyam continue to trade more relative to those who did not have direct exposure to Satyam. Interestingly, net traded value now has a positive sign, instead of the negative sign immediately after the event (as seen in Table 3). This means that while immediately after the crisis, those exposed to Satyam sold a lot of shares, they reversed their trading behaviour, and actually *increased* their participation (on the intensive margin) within 60 days of the event.

5.8 What is the impact on portfolio?

In the previous section we find that treated investors do trade more intensely immediately after the Satyam event relative to control investors. However, the question of interest is, if this trading leads to sub-optimal portfolios, measured by under-diversification and

Table 8 Net traded value (60 days)

	Dependent variable:	
	NTV (Rs.)	NTV/Val (%)
	(1)	(2)
Treat	−28.409***	−0.03***
	(5.030)	(0.004)
Post	−688.743***	−0.7***
	(4.487)	(0.004)
Treat*Post	19.290***	0.1***
	(6.345)	(0.01)
Constant	215.403***	0.2***
	(6.895)	(0.01)
State FE	YES	YES
Observations	6,227,014	6,227,014
Residual Std. Error (df = 6226991)	2,876.082	0.031
Note:	*p<0.1; **p<0.05; ***p<0.01	

beta of the portfolio. Dorn and Weber (2013) show that there is clear shift during the financial crisis towards larger domestic (German) stocks, but also more towards stocks with higher idiosyncratic volatility.

For each treated and control unit, we measure the under-diversification and beta on each date for thirty days pre and post the event. For each date, the under-diversification and beta measures are estimated using the market model which uses the returns data for the last 250 days. Table 9 presents the DID regression results. Column (1) and (2) shows the results on under-diversification and beta respectively from a robust regression.

Table 9 Regression: Under-diversification and beta

	Dependent variable:	
	Underdiversification	Beta
	(1)	(2)
Treat	−4.861***	−0.007***
	(0.022)	(0.0003)
Post	1.373***	0.0001
	(0.020)	(0.0002)
Treat*Post	2.822***	0.057***
	(0.028)	(0.0003)
Constant	40.246***	0.957***
	(0.031)	(0.0003)
State FE	YES	YES
Observations	6,214,382	6,214,382
Residual Std. Error (df = 6214359)	18.105	0.185
Note:	*p<0.1; **p<0.05; ***p<0.01	

The table shows that treated investors had a lower beta, and were less under-diversified than control investors, consistent with the statistics in Table 1. Both under-diversification and beta were high post the event. The effect was statistically significant for the treated group post the event as is evident by the coefficient of β_3. This suggests that while differences between the treated and control groups on trading had ceased over a month, the impact on portfolio quality was more persistent. Those exposed to the Satyam shock, seemed to have become more under-diversified, and their portfolios had higher sensitivity to the market.

6 Threats to validity

An assumption in the current research design is that outcomes from the treatment and control group emanate from the Satyam outcome. In this section we address alternative explanations that might explain the fall in the net traded value. Two alternatives can be offered

- Some other event caused de-investment by the treated group
- Unobservables between the treatment and control group are driving the result.

6.1 Was it some other event?

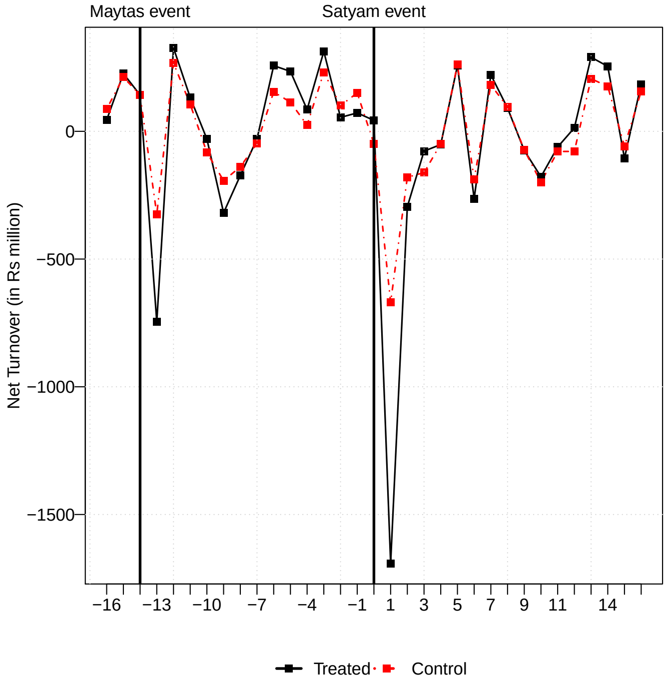
A possible criticism is that some other event around the time that caused the drop in traded value. For example, it is possible that it was the financial crisis of 2008 that is the cause of the sharp de-investment.

One way of testing if the cause of the decline was the Satyam event is to emulate another placebo where the DID is carried out on the treatment and control observations *before* the actual Satyam event. If the treated investors are not de-investing prior to the event, then we can be reasonably certain that the results are not driven by prior de-investments. We find that β_3 in such an exercise is not negative and statistically significant.[10]

In Figure 9 we present graphical evidence of the net traded value over a 30 day period. This includes the Mytas event discussed earlier. We find that around the Mytas event, the treated group de-invested more than the control group, but then, was roughly the same as control group upto the Satyam event, when the net traded value fell dramatically.

[10]The result is available on request

Figure 9 Net traded value over a 30 day period



6.2 Unobservables driving the result

Another criticism of the analysis could be that there are unobservable differences between the treated and control group that are driving the behaviour, and not the Satyam event. 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.

One way of testing the importance of unobservables is to observe the difference between those who owned Satyam on the day of the event, and those who did not own Satyam on the event but had owned it earlier. These are investors in the "control" group in the regression, but given that they had once held Satyam, could be considered to be more similar to the treated group than those who had never held Satyam. Table 10 presents the results. Here too, we see that Satyam investors de-invested more than non-Satyam investors, even though the coefficient is much lower (in rupee value) than those presented in Table 3. This suggests that it is not just unobservables that are driving the result.

Table 10 Restricting control group to those who once held Satyam

	Dependent variable:	
	NTV (Rs.)	NTV/Val (%)
	(1)	(2)
Treat	234.814***	0.5***
	(46.598)	(0.0003)
Post	−5,525.820***	−3.9***
	(55.201)	(0.0004)
Treat*Post	−555.548***	−1.2***
	(57.496)	(0.0004)
Constant	2,386.222***	1.5***
	(51.102)	(0.0003)
State FE	YES	YES
Observations	568,795	568,795
Residual Std. Error (df = 568772)	4,554.330	0.030
Note:	*p<0.1; **p<0.05; ***p<0.01	

7 Conclusion

In this paper we study the impact on investor behaviour of fraud revelation. We 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? We use daily holding data from the National Stock Depository Limited (NSDL), and a matching methodology to compare investors directly exposed to fraud with investors who were not directly affected.

Results suggest that investors with direct exposure trade more intensely over six days after the event relative to control investors, and that this trading is largely driven by cashing out of their portfolio. Within a month, however, treated investors cash-in into their portfolios. The impact on under-diversification is more persistent. So far, our results suggest that investors temporarily withdraw by way of sales of shares, but come back over a period of a month. The effect of fraud on investor trading seems to be short-lived.

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