

Accounting based regulation and earnings management

Radhakrishnan Gopalan , Xiumin Martin and Kandarp Srinivasan*

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Abstract

We document the distortionary effects of accounting-based regulation on reported earnings. In India only firms with negative book value of equity (networth) can seek bankruptcy protection. Using a novel dataset of bankrupt firms from India, we show that firms manage earnings *downward* to seek bankruptcy protection. Strengthening creditor rights reduces downward earnings management among non-group affiliated firms. Firms with income-decreasing pre-bankruptcy accruals have worse post-bankruptcy performance, suggesting that pre-bankruptcy accruals are a strong signal of opportunistic bankruptcy filing. We also find evidence for upward earnings management among firms with positive, but low networth in an effort to avoid bankruptcy filing. Overall, our paper underscores the importance of factoring economic incentives in designing regulation using accounting numbers. Validating our findings, the proposed new bankruptcy law in India does away with the accounting rule.

*The authors are from the Olin Business School, Washington University in St. Louis. They can be reached at gopalan@wustl.edu, xmartin@wustl.edu and kandarp.srinivasan@wustl.edu. We thank Viral Acharya, Nagapurnanda Prabhala and the seminar participants at CAFRAL and Moody's-ICRA-NYU conference on "Developing India's Fixed Income Markets for Sustainable Growth", seminar participants at Fordham University, Southern Methodist University for valuable comments.

Introduction

The use of accounting quantities for financial contracting is widespread. Most bank loan agreements include accounting statement based financial covenants (Smith Jr [1993], Dichev and Skinner [2002], Asquith et al. [2005], Ball et al. [2008]) and increasingly firms tie executive compensation to explicit accounting performance goals (Bennett et al. [2015]). A large literature studies the advantages and disadvantages of this practice (Lambert and Larcker [1987], Sloan [1993], Banker et al. [2012]). There is also increasing use of accounting quantities in designing regulation. Minimum capital requirements for banks are often stipulated in terms of book values. Product pricing is linked to reported profit (cost-plus pricing) for electric utility firms in the US. In China, from 1996 to 1998, the financial market regulator used accounting numbers to determine which firms can issue additional shares. The literature that studies the costs and benefits of such practices is nascent (Chen and Yuan [2004], Haw et al. [2005]). In this paper we study a setting in India where accounting numbers are used to determine when firms can obtain bankruptcy protection. Our objective is two-fold: First, we highlight distortions in accounting choice that can arise from such a regulation. Second, we examine the real economic consequences of such distortionary accounting. Given the sheer size of India's economy and the significant portion of industrial firms that are insolvent, the evidence in our study has important implications for both policy makers and researchers.

The setting we study is India's bankruptcy court, the Board of Industrial and Financial Restructuring (BIFR) during the time period 1990-2013. According to India's bankruptcy law (SICA¹ 1985), industrial firms in financial distress can register with the BIFR to effect a debt restructuring in consultation with lenders and equity holders. During this process, the equity holders remain in control of the firm's assets. There is a moratorium on all debt payments (Gopalan et al. [2007]) and all legal lawsuits against the debtor are suspended. The bankruptcy regime is extremely inefficient. Not only do the judges have a preference to keep firms alive in consideration for workers' interests but they also lack corporate expertise. Firms on average spend 7 years in the reorganization process (Kang and Nayar [2004]). Thus the bankruptcy proceedings not only allow inefficient firms to continue operating and destroy value but also provide a safe harbor for managers to tunnel firm assets and self-deal,

¹Sick Industrial Companies (Special Provisions) Act.

thereby exacerbating financial distress. Ahluwalia [2002] notes that the weak creditor rights environment in India makes it easy for managers to mismanage firms and divert resources to insiders.

A key aspect of the law that motivates our study is the way BIFR determines whether a firm is financially distressed. As per SICA (1985), an industrial firm is eligible to (and must) be registered with the BIFR if the accumulated losses are greater than the book value of equity contribution. In other words, a negative book value of equity (networth) is a necessary condition for industrial firms to file with BIFR.² Also, all industrial firms with negative networth are required to be registered with BIFR. Because negative networth might not be a necessary or sufficient indicator of financial stress, this can potentially result in two problems. On the one hand, financially distressed firms, even if they are out of cash to make debt payments, cannot seek bankruptcy protection unless their networth is negative. On the flip side, economically healthy firms can seek bankruptcy protection and stop making debt payments as long as their accumulated losses exceed the equity contribution. An immediate implication of the regulation is that it is likely to provide incentives for firms to manage earnings to effect their desired outcome to either seek or avoid bankruptcy protection.

Firms will manage earnings down through lower accruals and report losses if they wish to seek bankruptcy protection. This will happen both if the firm is truly distressed and needs the protection of the bankruptcy court to effectively restructure its debt or if the manager wants to exploit the inefficient bankruptcy court to defraud lenders.³ One can distinguish the genuine firms from the defrauders by studying subsequent performance. If genuine, we expect low accruals in the pre-bankruptcy period to be associated with better post-bankruptcy performance because effective restructuring during bankruptcy alleviates financial stress allowing firms to restore financial health. However, for defrauders, low accruals in the pre-bankruptcy period should be associated with worse post-bankruptcy performance because managers' self-dealing likely precipitates financial distress. Firms may also manage earnings up, especially if their networth is close to the zero threshold so as to avoid seeking bankruptcy protection. This can happen either if the firm is not financially

²Current thinking on bankruptcy eligibility has moved away from the negative net worth rule. According to India's draft bankruptcy bill (Insolvency and Bankruptcy Code 2015), whenever a corporate debtor is unable to repay debt that has become due, an operational creditor or the debtor himself may initiate the corporate insolvency resolution process. See detailed discussion in Section 8.5.

³Justice Eradi Committee Report (2002) estimates that nearly 20 percent of BIFR cases are dismissed on evidence of fraudulent behavior such as deliberate manipulation of financial statements.

distressed or is financially distressed but is in the process of effecting an out of court restructuring with its lenders (Gopalan et al. [2007]). We test these predictions along with a number of additional ones in our empirical analysis.

We obtain data from two main sources. The website of BIFR provides the list of firms that file for bankruptcy protection. Along with firm names, we also obtain the year the firm files for bankruptcy and the final outcome. We combine the bankruptcy data with financial data on Indian firms from Prowess, a data set maintained by the Center for Monitoring Indian Economy (CMIE). This dataset has been used by a number of prior studies on Indian firms, including Gopalan et al. [2007], Bertrand et al. [2002], and Gormley et al. [2012]. We obtain information on firm's income statement and balance sheet, along with ownership structure and industry affiliation.

In our first set of tests, we compare firms that eventually file with BIFR (bankrupt firms) to a set of control firms that we identify by matching on industry (2-digit NIC code), year, $\text{Log}(\text{Total asset})$ and Average ROA . All variables we use are defined in the Appendix. Specifically, for every bankrupt firm in our sample, three years before it files for bankruptcy, we identify up to two unique control firms from the same two-digit NIC code and financial year and that is closest in terms of the other two covariates. We use the Mahalanobis distance to identify the closest match. Our matching procedure is effective as the two samples are statistically indistinguishable with respect to $\text{Log}(\text{Total assets})$ and Average ROA in the year of matching.

We begin our empirical analysis by comparing the mean level of Abnormal accruals for the bankrupt firms and control firms around the bankruptcy event in Figure 1. We find a discontinuous decrease in the level of Abnormal accruals among the bankrupt firms starting two years before bankruptcy filing. Interestingly, the level of Abnormal accruals for the bankrupt firms return to normal levels three years after bankruptcy filing. Also, the level of Abnormal accruals are indistinguishable between the bankrupt and control firms in the years before the year of matching. This indicates lack of pre-trends. The abrupt fall in Abnormal accruals just before a firm seeks bankruptcy protection is consistent with firms managing their earnings down to seek bankruptcy protection.

We find that the fall in Abnormal accruals for bankrupt firms is robust to controlling

for other firm characteristics including firm, time and size-decile fixed effects. We find that our results are also economically significant. Firms that file with BIFR have 4.5% lower *Abnormal accruals* as compared to the control firms in the year before they file with BIFR. This result is robust to including all firms with financial data as part of the control sample and to confining the analysis to industries with at least one bankrupt firm. We also find that higher depreciation expense is one channel firms use to reduce their accruals and consequently their networth.

To ensure that our use of healthy firms as the control sample for firms that seek bankruptcy protection does not bias our conclusions, we do several robustness tests. First, we compare our sample of Indian bankrupt firms to firms that file for Chapter 11 bankruptcy protection in the U.S. We believe the U.S. firms that seek bankruptcy protection may provide an alternate and possibly more suitable benchmark for the Indian firms that file for bankruptcy. Since Chapter 11 does not have a networth condition for seeking bankruptcy protection, we expect the bankrupt U.S. firms to have higher pre-bankruptcy accruals than their Indian counterparts. Consistent with our conjecture, we find that firms that file with BIFR have lower *Abnormal accruals* relative to firms that seek Chapter 11 protection in the years before they seek bankruptcy protection. This offers further support consistent with firms underreporting earnings to satisfy the negative networth condition of BIFR.

Second, we benchmark the Indian firms that seek bankruptcy protection with a set of Indian firms that experience a steep (greater than 50%) fall in cash flows. If the fall in *Abnormal accruals* is due to a negative shock to firm profitability, then we expect the firms that experience a negative shock to cash flows to also have low accruals. Contrary to this, we find that the firms that experience a fall in cash flows have much higher level of *Abnormal accruals* than firms that do not experience a fall in cash flows or firms that seek bankruptcy protection through BIFR.

Finally, given that BIFR applies only to industrial firms, we look at the accrual behavior of non-industrial firms as a placebo test. We study *Abnormal accrual* behavior in the years before the net worth of non-industrial firms turns negative. In stark contrast to the industrial firms, we find that no statistical difference in the level of *Abnormal Accruals* for non-industrial firms. This result suggests that negative net worth, in and of itself, does not (mechanically) result in low abnormal accruals. Our evidence points towards opportunistic

behavior only in those firms that are eligible to take advantage of the accounting rule under the BIFR system.

During our sample period, India passed the Securitization and Reconstruction of Financial Assets and Enforcement of Security Interests Act (SARFAESI) in 2002 that gave secured lenders greater powers to get access to their collateral and increased the likelihood of restructuring outside BIFR.⁴ Consistent with this, we find a fall in the number of firms that file with BIFR after the passage of the SARFAESI Act. When we compare the level of *Abnormal accruals* of firms that file with BIFR before and after SARFAESI, we find that firms that file after SARFAESI have (weakly) higher pre-bankruptcy *Abnormal accruals* relative to firms that file before. This is consistent with SARFAESI making it difficult for firms to opportunistically seek BIFR protection. When we differentiate firms based on their group affiliation, we find that the effect of SARFAESI on *Abnormal accruals* is only present for non-group firms.

Related party transactions of BIFR firms could either represent a channel for earnings management or act as a potential mechanism to tunnel assets out of the firm. We find suggestive evidence along both dimensions. First, related party transactions of BIFR firms significantly increase just before the firm files for bankruptcy consistent with related party transactions facilitating earnings management. Second, group firms tend to have higher related party transactions than non-group firms in the years following bankruptcy filing which is suggestive of business groups using related party transactions to tunnel assets from bankrupt firms.⁵

The mandatory nature of the networth rule implies that firms with negative net worth need necessarily file with BIFR. Since filing with BIFR may not be optimal for all firms, we expect firms that wish to avoid bankruptcy to manage their earnings upward. We obtain two pieces of evidence consistent with this conjecture. First, we find a discontinuity in the distribution of firms around the zero networth threshold. A disproportionate number of firms have small positive networth as compared to the number of firms with small negative

⁴Relatedly, the Reserve Bank of India established the Corporate Debt Restructuring (CDR) system in 2001 to aid financial institutions in debt recovery. Cases referred to this non-statutory body were kept outside the purview of BIFR. Both the SARFAESI law and the CDR system strengthened creditor rights. We discuss this further in sections 2 and 6.2

⁵Due to lack of information on the amounts involved in the related party transactions, we confine our analysis to studying the number of related party transactions

network. This is consistent with firms managing their network to stay on the positive side. We follow the procedure in McCrary [2008] to show that the discontinuity is statistically significant. Second, when we focus on abnormal accruals, we find that firms with small positive network have significantly higher abnormal accruals. These results are consistent with the network based bankruptcy rule distorting reported earnings in both directions - While some firms understate network to seek bankruptcy protection, others overstate network to avoid bankruptcy.

Finally, we examine whether accounting distortions documented so far have real economic consequences. In order to do this, we relate the level of *Abnormal accruals* in the pre-bankruptcy period to performance measures such as ROA, Cash flows and Revenue subsequent to bankruptcy filing. We find a strong positive association between pre-bankruptcy accruals and subsequent performance - Firms with low pre-bankruptcy accruals have poor subsequent performance. This is consistent with pre-bankruptcy accruals being a good signal of opportunistic bankruptcy filing, which then is reflected in poor post-filing performance. As an interesting contrast, we do not find any systematic relationship between pre-bankruptcy *Abnormal accruals* and subsequent performance for U.S. firms. Our main results are robust to various alternative matching criteria. We also hand-collect information on the exact filing date to study stock market reactions to bankruptcy filing for listed BIFR firms. We find abnormal returns are 1% lower for firms with low pre-bankruptcy accruals as compared to firms with high abnormal accruals pre-bankruptcy. This result is consistent with opportunistic behavior by insiders leading to adverse economic consequences.

To summarize, the bankruptcy regulation based on network results in opportunistic earnings management by Indian firms. Firms that wish to seek bankruptcy protection record earnings decreasing abnormal accruals to depress their network. The income decreasing accruals are associated with worse performance during bankruptcy. On the other hand, firms that wish to avoid bankruptcy protection record earnings increasing accruals to boost their network. Overall, our paper highlights significant distortions in firms reported financial statements arising from attempts to time the bankruptcy decision and the consequent adverse economic effects such choices have on the firms.

We make a number of important contributions. First, we highlight the distortions that arise from designing regulations based on accounting numbers and discuss the associated

adverse economic consequences. We show that factoring economic incentives is critical in the design of accounting based regulation. Interestingly enough, the new bankruptcy law being proposed in India does not include the networth rule to decide eligibility to file for bankruptcy. Second, our research adds to the growing evidence on tunneling in emerging markets (Jiang et al. [2010]; Atanasov et al. [2010]; Nenova [2005]; da Silva and Subrahmanyam [2007]). We show how firms may take advantage of inefficient regulation through accounting manipulation and tunnel value through related party transactions. Finally, we add to recent research on creditor rights in emerging markets (Vig [2013], Visaria [2009]). Improvements in creditor protection results in less opportunistic behavior by insiders.

Our earnings management study around a regulatory threshold is closest in spirit to Haw et al. [2005] and Chen and Yuan [2004] who show Chinese listed firms manage earnings to meet a minimum ROE requirement to issue seasoned equity. Further, these papers (including ours) use an emerging markets setting to study firm accrual behavior. However, our paper is distinct in terms of analyzing real economic consequences to such earnings management. Using unique data on distressed firms, our study documents the real economic impact of distortionary accounting practices. Our main message is that poor design of regulation not only leads to perverse accounting behavior but also results in negative real effects such as asset tunneling.

1 Literature Review

A large body of accounting literature provides evidence that managers use accruals to manage earnings in various settings. Jones [1991] shows that petitioning firms during anti-dumping investigation periods have incentives to manage their accounting data to increase their probability of winning trade cases. Subsequent research finds that managers use abnormal accruals to manage earnings to maximize CEO compensation (Healy [1985]; Gaver et al. [1995]; Bergstresser and Philippon [2006]) and that earnings restatements are more common at firms where CEOs have larger options portfolios (Burns and Kedia [2006]). Teoh et al. [1998a,b] find that firms manage their earnings up before initial public offerings and secondary public offerings. They also show that earnings management is negatively associated with future stock performance, implying that investors do not fully see through

the earnings management. Market pressure and debt contracts may also give rise to earnings management. Firms may manage earnings to meet or beat analyst forecasts or to avoid covenant violation (DeFond and Jiambalvo [1994]; Dichev and Skinner [2002]). In this paper, we focus on bankruptcy regulation-induced earnings management. We also examine the economic consequence of these aggressive accounting choices.

Our paper also contributes to the literature on tunneling in emerging markets. Based on a sample of Bulgaria firms, Atanasov et al. [2010] demonstrate that weak legal protection of minority shareholders allows controlling shareholders to engage in equity tunneling through freeze outs and dilutive equity offerings. Nenova [2005] and da Silva and Subrahmanyam [2007] examine how changes in Brazilian rules providing takeout rights to common shares during freeze outs affect controlling shareholders' incentive to tunnel. Our study offers some evidence consistent with firms' insiders tunnelling assets via related party transactions during the bankruptcy process.

Our work adds to the literature on consequences of accounting rule-based regulation. From 1996 to 1998, listed companies in China were required to achieve a minimum return on equity (ROE) of 10% in each of the previous three years before they could apply for permission to issue additional shares. Haw et al. [2005] show that firms whose ROEs are in the 10 to 11 percent range have higher income-increasing abnormal accruals and non operating come than other firms. Relatedly, Chen and Yuan [2004] show that ROE is just above 10 percent in a disproportionately large number of instances in each of the three years before a rights offering. They also show that firms with high non operating income and ROE close to 10 percent subsequently underperform.

Finally, our paper extends the work on creditor rights in emerging markets. Vig [2013] uses a law aimed at strengthening creditor rights, SARFAESI, to study the impact on the corporate debt structure. SARFAESI empowered creditors to bypass the lengthy court process and seize collateral. Vig [2013] finds that, on average, secured debt (as a percentage of assets) falls by 5.0% after passage of the SARFAESI Act and argues that strengthening of creditor rights can impose costs on the borrower. We use the SARFAESI law to study the effect on accruals management and post-bankruptcy outcomes.

2 Institutional Background

There is no single comprehensive legislation on corporate bankruptcy in India. Various issues related to corporate insolvency are dealt under various laws. As a result, four different agencies have overlapping jurisdiction: the High courts, the Company law board, the BIFR, and the Debt recovery tribunals. The Companies Act 1956 was the first Indian constitution that governed the insolvency proceedings of modern Indian economy. Under the 1956 Act, a company was deemed unable to pay a debt if the company is unable to pay the debt exceeding rupees five hundred after expiry of three weeks from the date of issuing of the notice claiming the payment by the creditor. Under the Companies Act, if a debtor owes a creditor a sum exceeding rupees 500 and the creditor has served on the debtor a notice demanding payment, the creditor can approach the court for an order of winding up. However, the debtor may make a compromise or an arrangement with the creditors by reorganizing the share capital under Sec. 391 of the Companies Act. If it is proved to the court that the company is unable to pay its debt, an order for the winding up of a company may be made. In order to obtain an order for winding up on this ground, it has to be shown that the company is “plainly and commercially insolvent” Mitra [2001]. There are other modes of winding up which are voluntary and subject to the supervision of the court.⁶

The Sick Industrial Companies (Special Provisions) Act (SICA), 1985 established a government agency to help revive financially distressed (“sick”) enterprises.⁷ This quasi-judicial body, known as the Board for Industrial and Financial Reconstruction (BIFR) became operational in May 1987. The objective of BIFR was to ensure timely intervention and revival of distressed firms in the spirit of Chapter 11 bankruptcy in the US, symbolizing an improvement over existing inefficient legal systems. BIFR was empowered to investigate a firm’s sickness and approve restructuring plans for firms that had a reasonable likelihood of emerging from financial distress. BIFR defined a company as “sick” based on whether, at the end of any financial year, accumulated losses equal or exceed its entire net worth

⁶Voluntary winding up of a company may happen either by members or by creditors. Members’ voluntary winding up is when a company may wind up by passing a special resolution, submitting a statement of solvency and appointing one or more liquidators for such purpose. Creditors’ voluntary winding up is when the members of the company, resolving for voluntary winding up, cannot submit a certificate of solvency. The voluntary winding up procedure is then regulated by creditors with the help of a liquidator. Both types of winding up are cost and time efficient modes of liquidation. Mitra [2001]

⁷The agency was placed under the purview of the Ministry of Finance of India.

(i.e. net worth turns negative). The adequacy of this definition is highly questionable. As noted in Mitra [2001], this is not “an initial sickness stage [but] is simply the final *coramin* state”. In cases where there was no hope of recovery, the agency could recommend (to the respective High Court) that the firm be wound down.

Although established to enable swift resolution, BIFR rarely achieved its lofty goal in practice. Several legal scholars and practitioners have highlighted BIFR’s inefficiencies. Perhaps the most common criticism of the BIFR process was the extent of delays in the resolution process and the prevalence of opportunistic borrowers defrauding lenders. As noted earlier, Kang and Nayar [2004] estimate an average time of 7 years for BIFR to recommend reorganization of a distressed firm, which is significantly longer than the average of two years for U.S. firms (Bris et al. [2006]). More importantly, the authors note that firms are allowed *to contest actions prescribed by BIFR* in the courts. In return, the courts frequently refer the case back to BIFR (presumably due to lack of expertise) resulting in a never-ending cycle of inefficiencies and delays. During this time, there is a moratorium on debt payments, all legal lawsuits against the debtor are suspended, and the equity holders (read insider) remain in control of the firm.

Van Zwieten [2015] points out that the end result of this “rescue imperative” was to elongate resolution times, even for those cases that were clearly found non-viable early in the BIFR process. Legal experts (Batra [2003]) highlight that BIFR’s inefficiencies have turned it into a “haven for defaulting borrowers” whose sole purpose is to deflect creditors. Van Zwieten [2015] quotes from a report on Indian insolvency that succinctly describes the motivation of borrowers who seek BIFR shelter: “to extract whatever worth remains in the asset”.

Overall, the bankruptcy process imposes significant costs on lenders and leads to a loss of a significant portion of firm value. First, once a firm files for bankruptcy, there is an automatic stay on all legal proceedings until BIFR decides whether the firm is truly insolvent and unable to repay its debt. The automatic stay, like Chapter 11 in the U.S., prevents creditors from taking any legal action against the borrower until the filing is resolved. Second, creditors must be actively involved during this process, and it usually takes a year, on average, for the BIFR to decide whether the firm is truly insolvent and to be admitted for the restructuring/liquidation process. Third, the combination of long delays

and the automatic stay on legal proceedings creates incentives to default, and about 30% of the filings made to the BIFR are eventually dismissed because the firms are not truly insolvent (Gormley et al. [2014]). It is widely accepted that the bankruptcy system has been abused by firms seeking to avoid their creditors. By avoiding debt payment in bankruptcy, opportunistic borrowers can selectively sell assets or pay back loans to related parties. These self-dealing activities not only transfer wealth from lenders to insiders, but also undermine the ability of the firm to remain a going-concern, resulting in loss of value.

As expected, these inefficiencies have an adverse effect on the performance of India's banks, the primary lenders to industrial companies. To remedy this situation, the Government of India passed the SARFAESI in 2002 to allow banks to recover collateral from defaulted loans.⁸ SARFAESI strengthened creditor rights because it allowed them to bypass BIFR and seize assets and auction them to aid recovery of loans. By design, SARFAESI voided the automatic stay provisions of BIFR.

Parallely, in the spirit of assisting creditors, the Reserve Bank of India established an out-of-court restructuring mechanism for financially distressed firms. The Corporate Debt Restructuring (CDR) system, established in 2001, was a voluntary non-statutory body outside the purview of the BIFR. CDR covered firms with multiple banking accounts and outstanding exposure of INR 100mn or above. CDR enabled multiple financial institutions to coordinate their efforts and minimize losses in the recovery process. Both SARFAESI and CDR strengthened creditor rights by providing speedy alternatives to the in-court process. The SICA 1985 has been repealed and is placed under part VI A of the Companies Act, 1956 by the amendment Act of 2002 and under Chapter XiX of the Companies Act 2013. However, legal scholars argue that there were hardly any changes in the insolvency provisions to improve outcomes for creditors under the Companies Act 2013.

With this institutional backdrop, we begin our study of the bankruptcy system and the economic incentives it generates for firms.

⁸Prior to SARFAESI, following the recommendations of the Committee on the Financial System (Narasimham Committee) the GoI enacted the Recovery of Debts Due to Banks and Financial Institutions Act (RDDBFI), in 1993. The Act established two types of agencies, Debt Recovery Tribunals (DRTs) and Debt Recovery Appellate Tribunals (DRATs) and conferred upon them special powers for adjudication of debt recovery matters. These were fast track courts that were designed to reduce the load on India's overburdened court system. Since a BIFR filing introduced an automatic stay on the proceedings on DRT as well, they had a limited effect on the functioning of the BIFR.

3 Hypotheses Development

In this section we outline the hypotheses relevant to our setting. Only firms with accumulated losses greater than equity contribution i.e., negative networth, can register with BIFR. To the extent the networth does not reflect the true financial condition of the firm, this rule can provide incentives for firms to manage their earnings. Firms that wish to seek bankruptcy protection may engage in income-decreasing earnings management to depress the networth so as to make them eligible to seek bankruptcy protection. This will happen if the firm is truly distressed and needs the protection of the bankruptcy court to effectively restructure its debt. This will also happen if the manager wants to exploit the inefficient bankruptcy court to defraud lenders because managers can be sheltered from legal proceedings and from creditors' pressure for debt payment. This forms our first prediction.

Prediction 1: Industrial firms that seek bankruptcy protection with BIFR will have lower discretionary accruals in the years immediately before they file.

As mentioned before, the SARFAESI Act of 2002 gave powers to secured creditors to override automatic stay provisions under SICA 1985 and seize assets of a firm that has defaulted on its debt obligations. As documented by Vig [2013], SARFAESI was effective in enabling out of court debt restructuring. To the extent SARFAESI made it difficult for firms to opportunistically report negative networth and seek BIFR protection, we expect:

Prediction 2: Industrial firms that seek bankruptcy protection with BIFR post-SARFAESI will have higher discretionary accruals than firms that seek BIFR protection pre-SARFAESI.

An important aspect of the networth rule in SICA is that any industrial firm with negative networth on its books has to *compulsorily* file with BIFR. Firms with negative book value of equity may want to avoid filing with BIFR for two reasons. First, if the firm is not financially distressed but has low networth, filing with BIFR may pose an unnecessary administrative burden on the managers that they may wish to avoid. Second, even if the firm is financially distressed, to the extent lenders prefer an out of court debt reorganization, the firm may wish to avoid filing with BIFR so as to preserve its reputation with its lenders (Gopalan et al. [2007]). So firms whose networth is positive but small may manage accruals so as to avoid reporting negative networth and registering with BIFR. This would predict a

disproportionate number of firms with small positive networth as compared to the number of firms with small negative networth. Such firms with small, positive networth are also likely to have higher accruals.

Prediction 3: A disproportionately large number of industrial firms will have networth just greater than zero as compared to the number of firms with networth just less than zero. Firms with small, positive networth will have higher discretionary accruals.

A firm will understate its earnings, report negative networth and seek bankruptcy protection both if it is truly distressed and needs the protection of the bankruptcy court to effectively restructure its debt and if the manager wishes to exploit the inefficient bankruptcy court to defraud lenders. One can distinguish the genuine firms from the defrauders by studying subsequent performance. Genuine firms should benefit from the bankruptcy process. The level of accruals in the pre-bankruptcy period may indicate the firm's need for bankruptcy restructuring. This would predict that low accruals in the pre-bankruptcy period should be associated with better subsequent performance. On the other hand, if firms understate accruals to enter bankruptcy and defraud lenders, then low accruals in the pre-bankruptcy period will be associated with worse subsequent performance. This is because insider self-dealing during the bankruptcy process is likely to exacerbate financial distress and undermine the firm's ability to exit as a viable going-concern. We relate a firm's accruals in the year before it files with BIFR to its subsequent performance to test these contrasting predictions.

Prediction 4: Lower discretionary accruals in the year before a firm files with BIFR will be associated with better operating performance in the post-BIFR period.

Prediction 4 - alternate: Lower discretionary accruals in the year before a firm files with BIFR will be associated with worse operating performance in the post-BIFR period.

4 Data

4.1 Data Description

We obtain data for our analysis from four different sources. We obtain a list of all firms that file with BIFR from 1990 to 2013 from their website.⁹ BIFR's website provides the list of firms that file for bankruptcy protection along with the year the firm files and the current status. We combine the bankruptcy data with financial data on Indian firms from Prowess, a data set maintained by the Center for Monitoring Indian Economy (CMIE). Prowess provides annual financial data and other descriptive variables for firms, including their industry classification, year of incorporation, and group affiliation. Prowess is a panel of both listed and unlisted public limited companies with assets plus sales greater than Rs 40 million. It covers between 2,000 to 6,000 listed and unlisted firms each year, and about twenty-five percent of the firms are unlisted firms. Prowess provides detailed information from the firm's balance sheet and income statements. The data coverage of Prowess becomes more comprehensive in the later years of the sample.

Since data from the BIFR website does not have company identifier information (to link with Prowess), we do a text-based match between the two data sets using company names. We use a combination of manual as well as string-based matching using software tools. For strings matched by software, we manually parse through the matched list in order to ensure there are no discrepancies. At the end of the procedure, we are able to obtain financial data for nearly 1,700 firms that file for bankruptcy.

We obtain a list of U.S. firms that file for Chapter 11 bankrupt protection from the UCLA-LoPucki Bankruptcy Research Database. This database contains information on large (assets greater than \$100 million) public companies that file for bankruptcy since 1979. We combine this data with financial information from Compustat and construct key variables used in the analysis.

⁹<http://www.bifr.nic.in>.

4.2 Summary Statistics

In Table 1, we present the year-wise distribution of our sample of Indian firms. The column titled *Firm universe* presents the total number of bankrupt and non-bankrupt firm observations. The column titled *Bkrpt firms* provides the number of firms that file for bankruptcy protection during the year that we are able to match with Prowess. Thus in 1997, 105 firms in our sample file for bankruptcy protection. We have a total of 1,702 firms that file for bankruptcy protection during our sample period that we are able to match with Prowess. *Matched bkrpt firms* presents the subset of bankrupt firms for which we have non-missing financial data, obtain control observations and include in our final sample. For example, for the year 1997, we only have 55 of the 105 firms in our final sample. Overall, we are able to include 868 of the 1,702 bankrupt firms in our final sample. The main reason for fewer bankrupt firms in our final sample is lack of financial data for the pre-bankruptcy period. We find that only 59% of the bankrupt firm sample (1001 out of 1,702 firms) have non-missing financial data for at least three years before they file for bankruptcy. Of these firms with non-missing financial data, we include 87% of the firms in our sample (868 out of 1001). The reason for missing out on the 13% of firms is lack of non-bankrupt control observations from the same industry and financial year as the bankrupt firm.

From column (2) in Table 1 we see that the annual number of bankruptcies declines during the second half of the sample period. As explained above, part of this decline is due to SARFAESI Act of 2002 that made out of court debt reorganization easier. The column titled *Percentage included* provides the fraction of bankrupt firms that we include in our sample every year. We find the percentage to be lower in the first half of our sample period than in the second half. This reflects the poor data coverage in Prowess during the earlier part of our sample period. To control for this, we repeat our analysis after dropping the first few years from our sample.

In Table 2 Panel (a) we provide the summary characteristics of the bankrupt firms and the full Prowess sample. The table groups variables into three categories: matching variables, control variables and outcome variables. Note that although we do not perform any matching yet, we group the variables in this manner to highlight the large differences between the bankrupt firms and the full Prowess sample along observable dimensions. The

matching variables are $\text{Log}(\text{Total Assets})$ and Average ROA . We find that the average bankrupt firm is larger than the average firm in the full sample and has lower profitability as measured by ROA . Similarly, sales growth for the bankrupt firm is on average negative (-0.134) whereas it is positive for the full sample (0.042). The large differences between the bankrupt and the full Prowess sample highlights the importance of selecting a smaller subset of firms that look similar to the bankrupt firms as the control sample.¹⁰ Interestingly, our main outcome variable, Abnormal Accruals has similar values in the bankrupt firm sample and the full sample.

To test our predictions, we compare firms that ultimately file for bankruptcy with a control sample of non bankrupt firms. Specifically, for every bankrupt firm in our sample, three years before it files for bankruptcy, we identify up to two unique control firms from the same two-digit NIC¹¹ code and financial year as the bankrupt firm and that is closest in terms of $\text{Log}(\text{Total assets})$ and Average ROA during the previous three years. We use the Mahalanobis distance to identify the closest match. All variables we use are defined in Appendix. We identify these control firms three years before the firm files for bankruptcy and retain them throughout our analysis. To minimize the bias in our matching, we match with replacement so that the same control firm may be used for multiple bankrupt firms. Table 3 compares the treated bankrupt firm observations to the control firm observations. As mentioned earlier, we identify matches for 868 bankrupt firms. There are a total of 1,201 non-bankrupt firms in the control sample.

We notice that the median value of $\text{Log}(\text{Total Assets})$ and Average ROA are very similar for the treated (5.779 and 0.068) and control (5.82 and 0.074) samples. In the columns titled $p\text{-values}$, we formally compare the median values of the variables across the two samples and find that they are statistically indistinguishable (p-values of 0.62 and 0.22). Thus our matching procedure is effective in selecting a control sample of non-bankrupt firms that are observationally similar to the sample of bankrupt firms. We also compare the statistical distribution of the covariates between the two samples. We do this using a Kolmogorov-Smirnov test for the equality of distributions. We find that while the distribution of Average ROA is indistinguishable across the two samples, the distribution of $\text{Log}(\text{Total assets})$ is

¹⁰Using a performance measure such as Avg. ROA for matching also helps address concerns with the measurement of discretionary accruals (Kothari et al. [2005]).

¹¹National Industrial Classification, Ministry of Statistics and Programme Implementation, Government of India

marginally different with a p-value of 0.08. To control for this residual difference, we include size-decile fixed effects in our tests. In the last column, we compute the scaled difference statistic following Abadie and Imbens [2011]. As a rule of thumb, if the absolute value of the scaled difference statistic is more than .25, then linear controls may not be reliable (see Imbens and Wooldridge [2009] for further discussion). We find that the absolute value of the scaled difference is significantly smaller than .25 for the matching variables.

When we compare the control variables between the bankrupt and non-bankrupt firms, we find that the bankrupt firms have more tangible assets as measured by PPE (.428 as compared to .364), higher leverage (.535 as compared to .349), lower sales growth, lower value of sales as a proportion of total assets and less volatile cash flows as measured by the standard deviation of cash flows. To control for these residual differences, we use these variables as controls in our multivariate regressions. Although the medians are different, note that for all the control variables, the absolute value of scaled difference is less than .25. This indicates that linear controls will be adequate to control for the residual difference between the treated and control firms.

Table 4 provides the Pearson correlation coefficients between the key variables in our analysis. We find that larger firms, firms with higher *ROA*, firms with higher leverage, less PPE, faster sales growth, with sales as a higher proportion of total assets and those with more volatile cash flows have higher abnormal accruals. Given these strong correlations, we include these as controls in our regressions. We now proceed to describe our empirical strategy.

5 Empirical Methodology

To test our prediction, within the sample of bankrupt and control firms, we estimate the following model:

$$y_{it} = \beta_0 + \sum_{s=-5}^{-4} \Gamma_s \text{Pre-Bankruptcy}(-s)_{it} + \sum_{s=-2}^0 \Gamma_s \text{Pre-Bankruptcy}(-s)_{it} + \sum_{s=1}^5 \Gamma_s \text{Post-Bankruptcy}(s)_{it} + \gamma X_{it} + \delta_i + \delta_t + \varepsilon_{it} \quad (1)$$

where *Pre-Bankruptcy(-s)* (*Post - Bankruptcy(s)*) is a dummy variable that takes a value one if it is 's' years before (after) the bankruptcy filing by firm 'i' and zero otherwise. We confine the sample to five years before and five years after bankruptcy filing. The model is fully saturated with the three years before bankruptcy filing as the excluded category. That is we do not include *Pre - Bankruptcy(-3)*. Therefore, the coefficients on *Pre-Bankruptcy(-s)* (*Post- Bankruptcy(s)*) compare the level of the dependent variable 's' years before (after) the bankruptcy filing, to the three years before bankruptcy filing. Note that we match the treated and control firms three years before bankruptcy filing. Financial years for Indian firms typically extend from April-Mar. The fiscal year in Prowess identifies the financial year that ends as of March of a calendar year. Since we only know the calendar year when the firm files for bankruptcy, we refer to the fiscal year that ends as of March 31st of the year after the calendar year when the firm files for bankruptcy as year 0. For example, if a firm files for bankruptcy in year 2006, we code the fiscal year that ends as of March 2007 as year 0.

In these tests, we also include a set of control variables, X_{it} , from prior literature (Hribar and Craig Nichols [2007]; Dechow et al. [2012]) that are shown to be related to the level of abnormal accruals. These include *PPE*, *Leverage*, Δ *Sales*, *Sales* and *St. dev (CFO)*. We control for firm size in a non-parametric manner by including a set of ten size decile dummy variables. The standard errors we report are robust to heteroskedasticity and clustered at the two-digit NIC code level. Note that instead of just documenting the time-series changes in the level of *Abnormal accruals* as a firm approaches bankruptcy, we include a control sample and compare the level of accruals for the bankrupt and non-bankrupt firms because it allows us to adequately control for time trends in bankruptcy filing and accruals through the inclusion of year fixed effects.

To perform cross sectional tests, we estimate a modified model where we collapse *Pre - Bankruptcy(-5)* and *Pre - Bankruptcy(-4)* into a single dummy variable, *Pre - Bankruptcy (-5,-4)*. Similarly, we combine all the *Post-bankruptcy* dummy variables into one dummy variable, *Post - Bankruptcy*, that takes a value one for the years after the firm files for bankruptcy. In these tests *Pre - Bankruptcy (-1)* is our main variable of interest and its coefficient measures the extent to which *Abnormal accruals* is different for firms that file with BIFR in the year just before they file for bankruptcy. In our cross-sectional tests,

we include interaction terms between *Pre - Bankruptcy (-1)* and *Pre-bankruptcy (0)* and cross-sectional variables of interest. We describe these in greater detail in Section 6.

In our second set of tests, we relate the abnormal accruals before a firm files with BIFR to the post-bankruptcy performance using the following model.

$$y_{it}^{post} = \beta_0 + \beta_1 \text{Pre bankruptcy accruals}_{it-1} + \gamma X_{it-1} + \delta_j + \delta_t + \varepsilon_{it}$$

where y_i^{post} is the 3-year average, ROA, Cash Flow or Sales following bankruptcy. We confine the sample to firms that file for BIFR protection. *Pre bankruptcy accruals* refers to discretionary accruals measured in the pre-bankruptcy year t-1. We also include a set of control variables that may be correlated with firm performance. These include *PPE*, *Leverage*, Δ *Sales*, *Sales*, *St. dev (CFO)*, and *Cash flow*. We measure these variables in the pre-bankruptcy year t-1 and thus coincident with *Pre bankruptcy accruals*. We also include industry fixed effects (δ_j) and time fixed effects (δ_t) in this specification and report standard errors that are robust to heteroskedasticity and clustered at the industry level.

5.1 Identification Assumptions

We make two sets of assumptions to identify the extent to which firms reduce accruals before filing with BIFR. First, we assume that the treatment value (the effect of BIFR filing on abnormal accruals) is stable across units (the SUTVA assumption, Rubin [1978]). This assumption requires that the treatment status of any unit does not affect the potential outcomes of the other units and that the treatments for all units are comparable. In our setting, this implies that one firm’s decision to file with BIFR should not affect the response of other firms.

Second, conditional on the matching variables employed, we assume that bankrupt and control firms should have similar levels of *Abnormal accruals*. This is the conditional independence or unconfoundedness assumption. While there is no direct way to check the validity of this assumption, we perform several tests to assess the extent of bias due to unobserved heterogeneity. First, instead of healthy Indian firms, we compare the firms that file with BIFR to firms that file for bankruptcy under Chapter 11 in the U.S. This allows us to control for negative shocks that may both cause the bankruptcy filing and also result

in lower *Abnormal accruals*. Second, we estimate the Rosenbaum [2002] bounds to understand the extent of unobserved heterogeneity between the treated and control observations required to overturn our conclusions. We explain this in Section 8.4. Finally, we perform placebo tests using non-bankrupt firms that experience a drop in cash flows as well as firms ineligible to file for BIFR protection. We describe the results in Section 8.1 and Section 8.3.

6 Empirical Results

6.1 Earnings management around bankruptcy

We begin our empirical analysis by plotting the average level of *Abnormal accruals* for the bankrupt firms and control firms around the bankruptcy event in Figure 1. These represent the coefficients from a fully saturated model with separate dummy variables for the treated and control firms for the time period relative to the year of bankruptcy. The excluded category is three years before bankruptcy, which is the year we do the matching in. Thus the data point corresponding to year “t” can be interpreted as the difference in *Abnormal accruals* in year “t” relative to 3 years before bankruptcy. The red line represents the values for the bankrupt (treated) firms while the blue line represents the value for the control firms. The first thing to note is that for the years t-5 and t-4 there is no significant difference in the level of *Abnormal accruals* between the treated and control firms. Second, our comparison in Table 3 showed that in year t-3, there is no significant difference (p value of 0.71) in *Abnormal accruals* between the treated and control firms. Thus upto three years before filing for bankruptcy protection, treated firms have similar levels of *Abnormal accruals* relative to control firms. In contrast, we find a discontinuous decrease in the level of *Abnormal accruals* among the treated firms in the two years immediately before bankruptcy filing. Interestingly, the average level of *Abnormal accruals* for the treated firms return to normal levels three years after bankruptcy filing. This clearly highlights that firms that file for bankruptcy protection experience an abrupt decrease in *Abnormal accruals* just before they file for protection.

In Table 5, we perform our multivariate analysis by estimating equation (1) with *Abnormal accruals* as the dependent variable. We find that consistent with our graphical

evidence, the coefficient on *Pre-bankruptcy (-5)* and *Pre-bankruptcy (-4)* are insignificant. Thus there is no significant difference in the level of *Abnormal accruals* between the treated and control firms upto 3 years before bankruptcy filing. There is a sharp fall in the level of *Abnormal accruals* starting from two years before bankruptcy filing (coefficients are also economically significant). This trend reverses immediately after bankruptcy and becomes indistinguishable from zero two years after bankruptcy. The coefficient on *Pre-bankruptcy (-1)* indicates that one year before filing, bankrupt firms have 4.5% lower *Abnormal accruals* relative to the average value for the control firms. From the coefficient on the control variables (which we suppress here to conserve space), we find that firms with less tangible assets and sales (negative coefficient on PPE and SALES) and those with faster sales growth (positive coefficient on CHGSALE) have higher abnormal accruals. These coefficients are consistent with prior literature (Dechow et al. [2012]; Collins et al. [2012]).

In column (2), we repeat our tests after including all firms with non-missing data in the sample. Thus in this specification, we include all the bankrupt firms that we are able to match with Prowess and we do not confine the control sample to firms that look similar to the bankrupt firms. As a result, some of the non-bankrupt firms in this specification could look very different from the treated firms on observable dimensions and linear controls may not be adequate to control for those differences. Despite this, we continue to find that there is a decrease in the level of abnormal accruals for the treated firms starting two years before bankruptcy filing. Unlike the results in column (1), we find that the lower accruals of the bankrupt firms continues for upto five years after bankruptcy filing. Interestingly enough, our coefficient estimate on *Pre-bankruptcy (-2)* and *Pre-bankruptcy (-1)* are similar between column (1) and column (2). In column (3) we confine the sample to firms in industries with at least one bankrupt firm. Here again we find a fall in *Abnormal accruals* for the bankrupt firms starting two years before bankruptcy filing. Finally in column (4) we repeat our tests confining the sample to the post 2000 period. We do this because of poor data coverage in Prowess during the early part of our sample period. Here again we find a decrease in accruals among the bankrupt firms starting two years before bankruptcy filing. Thus we find that our main result in column (1) is very robust to significant changes in the underlying sample. Overall, the evidence in Table 5 confirms downward earnings management by BIFR firms just before they file for bankruptcy. This is consistent with *Prediction 1*.

In Table 6 we repeat our tests with *Depreciation* as the dependent variable. In column (1) we focus on our treated and control sample, in column (2) we include all firms, in column (3) the sample is confined to industries with at least one bankruptcy and column (4) is confined to the post-2000 time period. We find that in all the columns, the coefficient on Pre-bankruptcy (-1) is positive and significant. This indicates an increase in depreciation expense in the year before the firm files for bankruptcy. We also note that the size of the coefficient is similar across the four columns. This indicates firms use higher depreciation expense as a potential channel to understate their earnings.

6.2 Earnings management, creditors rights and group affiliation

In Table 7, we analyze how the SARFAESI Act affects *Abnormal accruals* behavior in firms that seek bankruptcy protection. To estimate the effect of SARFAESI, we repeat our tests after including a dummy variable, *SARFAESI* that takes a value one after passage of the law, i.e., for the years 2002-2013 and an interaction term, $SARFAESI \times Pre - bankruptcy (-1)$. We divide our sample into group-affiliated firms and non-group affiliated firms (Columns (1) and (2)) to study the interaction effect. From column (1) of Table 7, we find that the coefficient on the interaction term is not statistically significant. This suggests that, for group firms, SARFAESI likely had no effect in reducing the ability of firms to opportunistically seek BIFR protection. In Column (2) of Table 7, we estimate the effect of SARFAESI on accrual behavior pre-bankruptcy for non-group affiliated firms. Column (2) shows that the interaction term $SARFAESI \times Pre - bankruptcy (-1)$ is positive (0.036) and significant (t-statistic of 2.07). The positive sign indicates that passage of the SARFAESI law had the effect of mitigating downward earnings management by BIFR firms. In Column (3) we test if the difference between the coefficients estimated for the group and non-group firms is significantly different from zero. Due to noise in our estimation, we find that although the difference in coefficient is large in magnitude, it is not statistically different from zero.¹²

Finally, to see if SARFAESI is effective in eliminating the opportunistic behavior among non-group firms filing for BIFR protection, we test if the sum of the coefficients on *Pre-bankruptcy (-1)* and $SARFAESI \times Pre-bankruptcy(-1)$ is statistically different from zero for non-group affiliated firms. In Column (2), we find that the sum is not statistically different

¹²We also find no statistical differences between public and private firms in our sample

from zero (F-stat of 1.94). This indicates that for non-group firms, SARFAESI appears to have been effective in preventing opportunistic accrual behavior.

Around the same time as SARFAESI, the Reserve Bank of India established an out-of-court restructuring mechanism - the CDR (Corporate Debt Restructuring) system. Established in 2001, CDR enabled multiple financial institutions to coordinate efforts and minimize losses in the recovery process. Both the SARFAESI Act and the CDR system were aimed at strengthening creditor rights. Since they were implemented close together, we will not be able to differentially estimate the effect of each on the behavior of distressed firms. Our results with SARFAESI likely capture the combined effect of both SARFAESI and CDR.

6.3 Earnings management and network

6.3.1 Net worth discontinuity

In this section we study non-BIFR firms to test *Prediction 5*. Specifically we study the distribution of firms with network close to zero to test to see if there is any discontinuity in the probability density. As explained before, if firms manage their network to prevent it from becoming negative, then we expect a disproportionately large number of firms with small-positive network as compared to the number of firms with small-negative network. To test this, in Figure 3, Panel (a) we plot the density of firm's net worth scaled by total assets using the DCDensity procedure developed in McCrary [2008]. We plot the empirical density along with the 95% confidence interval and test for a discontinuity at zero. To study the behavior of firms close to the zero threshold, we focus attention on a small range (-0.05 to +0.05) around zero. The bin size for the plot is the default bin size estimated by the DCDensity function and is 0.0008. The figure shows a striking discontinuity at the threshold: a disproportionately large number of firms fall on the positive side of zero. The discontinuity estimate (log difference in height) is 0.665. The presence of a discontinuity at zero is consistent with firms managing their book value of network to prevent it from becoming negative. To ensure our results are not driven by the scaling factor, in Panel (b) of Figure 3, we use the reported value of network (in INR million) and repeat our density test. Here again we find clear evidence of discontinuity at the zero threshold indicating the

robustness of our result. Overall, our results are consistent with the negative network rule providing incentives for Indian firms to manage their network.

6.3.2 Abnormal accruals and net worth

In this section we focus on firms with small-positive network to test if they engage in positive earnings management using discretionary accruals so as to avoid filing with BIFR. In Figure 4, we plot the mean abnormal accruals for firms whose net worth is close to zero. Specifically, we use the bin size of .0008 from the DCDensity procedure from above and plot the average accruals of firms within each bin. Thus, bin1 refers to all firms whose (scaled) net worth value falls between zero and the bin width (0.0008), bin2 refers to all firms whose (scaled) net worth value falls between 0.0008 and 0.0016 and so on. Similarly, Neg bin1 refers to firms whose (scaled) net worth value falls between -0.0008 and 0. The vertical bars represent the *average* abnormal accruals for firms within each bin.

We find that average abnormal accruals is positive for firms that are closest to zero and is also significantly larger than that for firms in bin2. This is consistent with firms with net worth closest to zero managing their earnings upward. This is consistent with the firms trying to avoid filing with BIFR. As mentioned earlier, if the firm is not truly financially distressed, filing with BIFR may pose an unnecessary administrative burden. Even if the firm is financially distressed, the firm may wish to avoid filing with BIFR so as to preserve its reputation (Gopalan et al. [2007]) with lenders. In unreported tests, we repeat our analysis using the reported net worth value (in INRmn) instead of scaled network and again find that firms with small-positive network have higher abnormal accruals. The results in this section highlight that the network rule results in distorting firm earnings both in the positive and negative side.

In summary, the evidence in Figures 3 and 4 are an interesting counterpoint to our earlier tests on downward earnings management. We find that the average Indian firm (with low but positive network) tends to avoid the BIFR system by engaging in positive earnings management. On the other hand, from the results in Table 5 we see that firms that do want to file with BIFR engage in income decreasing abnormal accruals in an effort to seek bankruptcy protection.

It may be interesting to understand the specific ex-ante firm characteristics that differentiate firms that manage earnings upward from those that manage earnings downward. Unfortunately, designing such a test poses a number of issues. First, it is not obvious which firms to include in the sample. If we were to select a sample based on past networth being close to zero, we may miss some of the firms that engage in significant downward earnings management to file with BIFR. Furthermore the specific cut-off one should use is also not obvious as the cut-off from the DCDensity procedure results in too few firm observations. Including all the bankrupt firms and the non-bankrupt firms with small positive networth may also not be reasonable as not all firms with small-positive networth may engage in upward earnings management. Furthermore unobserved differences between the two groups of firms may drive the differences on observed characteristics. Hence we do not perform such a test.

6.4 Earnings management and related party transactions

In this section we study the number of related party transactions around the bankruptcy filing date to understand the extent to which firms use such transactions to manage reported earnings to reduce their net worth before bankruptcy filing. Our analysis will also help us understand if firms use related party transactions as a means to expropriate value from lenders during bankruptcy. Since we do not have the value of the related party transactions due to missing data, we confine the analysis to studying the distribution of the number of related party transactions around the time when a firm files with BIFR. In Figure 5, we plot the time-series distribution of the number of related party transactions of BIFR firms. The y-axis measures the average number of related party transactions to *insiders* (who we classify as key personnel, relatives of key personnel or any party where control exists). The x-axis in Figure 5 indicates the years before and after bankruptcy filing. Remarkably, we find that the number of related party transactions spikes just before bankruptcy. The time series shows a perceptible increase in the average number in T-1. The jump in average annual transactions from 32 in year T-2 to 50 in year T-1 is strongly statistically significant. The other striking pattern in Figure 5 is that the average number of related party transactions remain at high levels for upto three years after BIFR filing. In Figure 6, we plot the average number of related party transactions for group and non-group firms around bankruptcy filing. Figure

6 shows two interesting patterns: First, there is no significant difference between group and non-group firms in terms of the number of related party transactions before bankruptcy. Second, the number of related party transactions is vastly different in the years following bankruptcy. Group firms have a larger number of related party transactions in the post-bankruptcy period as compared to non-group firms. The difference between the two sets of firms is statistically significant. Our results are suggestive of group firms that declare bankrupt using related party transactions to tunnel value.

Overall, the results on related party transactions provide suggestive evidence of opportunistic behavior by insiders before as well as after bankruptcy filing¹³

7 Real effects

7.1 Post bankruptcy performance

The empirical results in the earlier section highlight the distortionary effects in accounting choice induced by the net worth rule. This raises a natural question: Is income-decreasing accrual behavior *efficient* from the firm's standpoint? One aspect of efficiency relates to the firm's own performance post-bankruptcy. For genuine firms that seek lender coordination during times of distress, bankruptcy filing may be efficient. Income-decreasing accruals that enable such a filing may ultimately benefit the firms and reflect in better performance. On the other hand if firms engage in income-decreasing accruals to file for bankruptcy and tunnel value and defraud lenders, then such accruals are likely to be associated with worse post-bankruptcy performance. In this section, we test these contrasting predictions. Specifically, we test whether accruals management in the pre-bankruptcy period is related to post-bankruptcy outcomes. In these tests our main independent variable is *Pre-bankruptcy accruals*, which measures the discretionary accruals in the year (T-1) before bankruptcy filing. We measure performance using average ROA, average cash flows and average sales over a three year post-bankruptcy period.

¹³In unreported tests, we look at transactions that involve *Payments* to insiders. Here again, we find that the number of payments to insiders jumps significantly in the year before bankruptcy. Interestingly, the average number of payments remain at high levels for upto 3 years after bankruptcy filing suggesting a channel for asset tunneling. We also repeat our analysis of the difference in group and non-group firms by comparing related party payments. Consistently, we find that group firms tend to increase payments to insiders post-bankruptcy.

In columns (1), (4) and (7) of Table 8 we confine the sample to Indian firms that seek bankruptcy protection with BIFR. We find that the coefficient on *Pre-bankruptcy accruals* is positive and significant after controlling for cash flows in column (1) and column (3). A 1% increase in pre-bankruptcy accruals raises Average ROA by 0.09%, Cash Flow by 0.02% and Revenues by 0.63%. More importantly, positive correlation indicates that *lower* pre-bankruptcy accruals is associated with *worse* post-bankruptcy performance. This is consistent with lower pre-bankruptcy accruals being a sign of opportunistic behavior from firms in seeking bankruptcy protection to defraud lenders.

In columns (2), (5) and (8) of Table 8 we repeat our tests in the subsample of U.S. firms that seek bankruptcy protection under Chapter 11. One can think of this as a placebo test. We do not expect to see a positive correlation between pre-bankruptcy accruals and post-bankruptcy performance for the U.S. firms. Consistent with our conjecture, in the U.S. sample, low accruals in the pre-bankruptcy period is not related to subsequent performance (expect in Column (5)). In columns (3), (6) and (9) of Table 8, we also estimate the difference between the coefficients for the Indian and U.S. samples. Here, we find strong evidence of significant differences between the two samples. This tells us that downward earnings management in the pre-bankruptcy period is associated with incrementally worse post-bankruptcy performance for Indian firms.

7.2 Market reaction

To better understand the real economic consequences of distortionary accounting practices, we turn to stock market reactions of bankruptcy filing. However, our current data set is inadequate because it lacks information on the calendar date of bankruptcy filing. To overcome this hurdle, we extensively search news articles, company announcements and business/economic commentary on publicly-listed bankrupt firms. We manage to hand-collect data on a total of 57 listed bankrupt firms for which information on the date of registration is publicly available. We perform an event study around the bankruptcy filing date for these firms using various event windows. Table 9 provides estimates. Not surprisingly, the market, on average, reacts negatively to news of bankruptcy filing (-0.47% over a 3-day horizon and -0.177% over a 10-day horizon). We now split our sample into firms with high and low pre-bankruptcy accruals, defined by the average *Abnormal Accruals* in the 5

years before bankruptcy filing. Interestingly, we find that average announcement returns are consistently negative only for those firms with lower-than-median pre-bankruptcy accruals. Furthermore, this difference is statistically significant implying a substantially large negative market reaction for firms with lower pre-bankruptcy accruals. Table 9 shows that the economic difference is greater than 1% in most cases. If insiders file for BIFR protection to take advantage of the system at the creditors' expense, such behavior leads to an average economic loss of 1% as measured by market values.

Overall, the results in this section suggest that low accruals in the pre-bankruptcy period is a sign of opportunistic behavior by insiders to defraud lenders, ultimately resulting in negative economic consequences.

8 Robustness Tests and Further Discussion

8.1 Alternate Control Samples

A genuine concern with our tests in Table 5 is the extent to which non-bankrupt firms can serve as an appropriate benchmark for firms that declare bankruptcy. The negative shock that prompts a firm to declare bankruptcy may also cause the negative accruals. To address this concern, we do a number of tests. First, we use a sample of firms that file for bankruptcy protection in the U.S. as a benchmark and compare the level of accruals for the two sets of bankrupt firms. Since the Chapter 11 in the U.S. does not have a negative-networth condition, bankrupt firms in the U.S. may not have the same incentives as Indian firms to report lower *Abnormal accruals*. On the other hand, to the extent bankruptcy in the U.S. is also a result of declining firm prospects, the level of abnormal accruals among U.S. firms that seek bankruptcy protection may represent the normal level of accruals of a firm with declining prospects.

In Table 10, we repeat our tests in the subsample of Indian and U.S. firms and compare the coefficient estimates across the two samples. In column (1) we present the results for the Indian sample. Consistent with our results in Table 5, we find a decrease in abnormal accruals for bankrupt firms starting two years before bankruptcy filing. In column (2) we estimate the same regression in a sample of U.S. firms. The sample for this estimation

includes firms that file for Chapter 11 bankruptcy protection in the U.S. and a control sample of firms from the same industry and closest in terms of $\text{Log}(\text{Total assets})$ and Average ROA three years before the firm files for bankruptcy. Interestingly, in the sample of U.S. firms, we do not find evidence of a decrease in Abnormal accruals in the year before the firm files for bankruptcy protection. U.S. bankruptcy code does not require firms to have negative net worth to file for bankruptcy protection. Hence, we should not expect U.S. firms to have strong incentives to manage earnings downward. In column (3) we present the tests that compare the coefficients across the Indian and U.S. subsamples. We find that consistent with our conjecture, the level of abnormal accruals is significantly lower for Indian firms in the two year period before the firm files for bankruptcy protection. The lower accruals among Indian firms is consistent with the negative networth criteria for BIFR prompting the firms to lower the level of accruals to ensure that they become eligible to seek bankruptcy protection.

In Table 11, we compare the level of cash flows of Indian and U.S. firms that seek bankruptcy protection. Unlike accruals, we do not find a difference in the level of cash flows across the two samples. In fact, the positive and significant coefficient on $\text{Pre bankruptcy} (-1)$ in Column (3) indicates that just before bankruptcy filing, relative to three years before bankruptcy filing, cash flows are significantly higher for Indian firms as compared to for U.S. firms. The negative coefficient in both Column (1) and Column (2) is consistent with both sets of firms experiencing a fall in cash flows in the pre-bankruptcy period that prompts the bankruptcy filing.

In Table 12, we compare the level of depreciation between Indian and U.S. firms that seek bankruptcy protection. Interestingly, we find that depreciation levels (relative to year T-3) are higher for Indian firms compared to U.S. firms beginning two years before bankruptcy filing. To the extent firms use depreciation expense as a lever to decrease reported earnings, this result is consistent with our conjecture that Indian firms have unique incentives for downward earnings management because of the net worth accounting rule.

In unreported tests, we rerun our main regression specification by choosing a control sample that experienced significant declines in cash flows. We choose our treated-control pairs such that the control firm experienced a steep (greater than 50%) decline in cash flows in year T: the year when the corresponding treated firm filed for bankruptcy under BIFR.

Again, we find evidence of downward earnings management in the years before bankruptcy filing. The observed decrease in discretionary accruals is unlikely a mechanical outcome resulting from cash flow pressures of distressed firms. Rather, the result points towards opportunistic behavior by bankruptcy filers to take advantage of the BIFR system.

8.2 Matching Criteria

To examine the robustness of our matching criteria, we perform three additional tests. First, we repeat our analysis in section 6.1 by changing the year of the match. Our existing matching procedure uses three years before bankruptcy as the year of the match. We change the matching year to two years before (we use T-2 instead of T-3) and find that our results are robust to this change. Second, we include *Leverage* as a matching criterion (in addition to matching on *Average ROA* and *Log (Assets)*). Third, we verify if our results hold by including *Abnormal Accruals* as matching criterion. In all cases, we find consistent results indicating that our main finding is robust to a variety of changes to the matching procedure. We do not present these results here to conserve space. They are available upon request.

8.3 Placebo tests

A possible concern with our comparison of Indian and U.S. firms is that some country specific difference in the accounting rules could affect the differences we observe. To address this, in Table 13, we study the behavior of *Abnormal accruals* of industrial firms that experience financial distress (we proxy distress by a steep (greater than 50%) fall in cash flows) but did not file under BIFR. We call this the pseudo-bankrupt sample. If the lower accruals among firms that file with BIFR is because of poor performance, then we should observe lower accruals (as in Table 5) in the pseudo-bankrupt sample as well. Our results from Table 13 do not indicate lower *Abnormal accruals* among firms that experience a steep fall in cash flows. On the contrary, we find a slight increase in the level of *Abnormal accruals* coincident with the fall in cash flows. The coefficient is positive and strongly significant. From the coefficient in Column (1) we find that *Abnormal Accruals* are 1.7% higher (relative to year t-3) among firms that experience a steep fall in cash flows as compared to the control sample. This result is very robust to changes in the underlying sample. In column (2) we

repeat our tests in the full sample (after excluding the bankrupt firms), and in column (3) we restrict the sample to industries that have at least one distress event. The stark contrast between BIFR firms (Table 5) and pseudo-bankrupt firms (Table 13) implies that BIFR firms opportunistically lower their abnormal accruals to take advantage of the regulatory shelter.

If poor performance (as captured by net worth going negative) drives discretionary accruals down, then we might still be concerned that our main result captures this mechanical effect rather than opportunistic behavior by firms who take advantage of the BIFR system. To address this concern, we perform another placebo test. We note that the BIFR system is designed to assist *industrial* firms. Hence, we choose non-industrial firms and study their accrual behavior to see if we find similar results. Specifically, we analyze accrual behavior of distressed firms that belong to services industries (Health Services, Courier Services, Transport and Logistics Services etc.)¹⁴ in the years before their net worth turns negative. Despite negative net worth, these firms are ineligible to file with BIFR. Hence, they are unlikely to have strong incentives to manage earnings (as they cannot seek BIFR protection). Table 14 shows regression results where we use year dummies to estimate accrual behavior before the negative net worth event. From the table we see that none of the pre-event dummies are statistically significant. Negative net worth, by itself, does not lead to the accrual behavior we observe in Table 5. Instead, the placebo test confirms that the accounting rule of the BIFR system creates unique (perverse) incentives for downward earnings management.

8.4 Caliper matching and Rosenbaum (2002) bounds

In Table 15, we estimate the Rosenbaum [2002] bounds to check the robustness of our matching procedure. A common limitation of matching methods is the difficulty in controlling for unobservables that may potentially bias estimates. In other words, selection into treatment may be non-random. The Rosenbaum [2002] procedure helps estimate the amount of unobserved heterogeneity required to undermine the conclusion of a causal effect. In Table 15, we provide an estimate of the Average Treatment Effect on the Treated (ATT) for our main outcome variable (*Abnormal Accruals*) along with the corresponding

¹⁴Our sample contains 657 firms in this category

Rosenbaum [2002] bounds. To estimate ATT we use caliper matching with a caliper size of 0.25. A bound of 1.8 for *Abnormal Accruals* indicates that the confounding factor should be strong enough to increase the odds ratio of being treated by 80% to overturn our main conclusion of lower abnormal accruals in the year before a firm files for bankruptcy. The relatively high value of Rosenbaum [2002] bounds indicates that our result is quite robust to unobserved heterogeneity.

8.5 Further Discussion

An endnote to our analysis is the changes that are being proposed to the bankruptcy resolution regime in India. The Government of India has proposed a new bankruptcy law called the Insolvency and Bankruptcy Code, 2015.¹⁵ One important difference between the new law and SICA is that the former does not have the networth rule to identify bankruptcy eligibility. As per the new law, insolvency (and eligibility for bankruptcy protection) is based on a firm's ability to service its debt. If a firm is unable to meet its debt obligations, either the debtor or the creditor can initiate insolvency proceedings. This new move is in the right direction and is a recognition of the distortionary effects of determining bankruptcy eligibility based on accounting quantities documented in our paper.

9 Conclusion

In this paper we examine the distortionary effects of accounting-based regulation on reported earnings. The setting we study is India's bankruptcy court, the Board of Industrial and Financial Restructuring (BIFR) during the time period 1990-2013. As per SICA (1985), a firm is eligible to (and must) be registered with the BIFR if and only if its networth is negative. Firms that wish to seek bankruptcy protection will manage earnings down through lower accruals and report losses. On the other hand, firms may also manage earnings up, especially if their networth is close to the zero threshold and they wish to avoid bankruptcy protection. We test for such distortion in our data.

When we compare firms that eventually file with BIFR (bankrupt firms) to a set of

¹⁵See <http://www.finmin.nic.in/reports/DraftInsolvencyBankruptcyBil2015.pdf> for more details

control firms that we identify by matching on industry (2-digit NIC code), year, $\text{Log}(\text{Total asset})$ and Average ROA , we find that the former experience a discontinuous decrease in the level of Abnormal accruals starting two years before bankruptcy filing. We find such behavior is present when we compare the Indian bankrupt firms both to a set of firms that seek bankruptcy protection under Chapter 11 in the U.S. and also to a set of Indian firms that experience a steep fall in cash flows. We find that non-group firms that file for bankruptcy after the passage of the SARFAESI Act have higher Abnormal accruals relative to firms that file before. BIFR firms tend to show high activity in related party transactions in the years just before and after bankruptcy. We also find a robust positive association between pre-bankruptcy accruals and subsequent performance. That is, firms with low Abnormal accruals pre-bankruptcy, have poor subsequent performance. This is consistent with low pre-bankruptcy accruals indicating opportunistic behavior by firms to defraud lenders. Finally we also find evidence for firms with low networth to engage in income increasing accruals so as to avoid crossing the zero networth threshold.

In summary, our paper documents the distortions that arise from a bankruptcy regulation based on networth in combination with firms' attempt to time their bankruptcy status. In emerging economies where creditor rights are weak and enforcement is lax, understanding economic incentives is crucially important in the design of regulations.

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Appendix:

Variable definitions

- *Treated*: A dummy variable that identifies observations for which there is at least one control firm in the matched sample.
- *ROA*: The ratio of EBITDA to average total assets.
- *Average ROA*: For any given year, *Average ROA* is defined as the average of the ROA variable over three years (current year, one year before, two years before). For the matching procedure, we match based on the *Average ROA* variable measured in year T-3, where T is the year of bankruptcy. This effectively means that the *Average ROA* used in matching is an average over the following three years: T-3, T-4 and T-5, where T is the year of the bankruptcy.
- *Leverage*: The ratio of the book value of long term debt to the book value of total assets.
- *PPE*: The ratio of net fixed assets (property, plant and equipment) to the book value of total assets.
- *CHGSALE*: The year-on-year change in sales divided by average (current, lagged) book value of assets.
- *SALES*: Revenues divided by lagged book value of total assets
- *AC*: Accruals defined as: $= \Delta \text{Current assets} - \Delta \text{Cash} - (\Delta \text{Current liabilities} - \Delta \text{short term debt}) - \text{Depreciation}$
- *STD(CF)*: Standard deviation (over a three year period) of Net Income - AC (scaled by assets)
- *Operating free cash flow*: defined as $= \text{Operating profit}(1-\text{tax rate}) + \text{Depreciation} - \Delta \text{Working capital}$

Abnormal Accruals

We measure *Abnormal Accruals* using the Jones model (Jones [1991]), as modified by Dechow et al. [1995]. We first estimate firm-specific normal level of accruals using the model:

$$AC_{it} = \beta_1 (1/Assets_{it-1}) + \beta_2 (\Delta \text{Revenue} / Assets_{it-1}) + \beta_3 (\Delta \text{PPE} / Assets_{it-1}) + \varepsilon_{it}$$

The above regression is estimated for each industry-year. The estimated coefficients are used to obtain firm-specific fitted values of normal accruals for all firms in our sample.

$$\widehat{AC}_{it} = \widehat{\beta}_1 (1/Assets_{it-1}) + \widehat{\beta}_2 (\Delta \text{Revenue} / Assets_{it-1}) + \widehat{\beta}_3 (\Delta \text{PPE} / Assets_{it-1})$$

Then we calculate Abnormal Accruals as the difference between fitted values and actual values of normal accruals. $Abnormal\ Accruals_{it} = AC_{it} - \widehat{AC}_{it}$

Table 1: **Distribution of corporate bankruptcies by filing year**

This table shows the distribution of bankruptcies in the sample period 1990 to 2013 by year of filing. *Firm universe* presents the total number of firm observations (both bankrupt and non-bankrupt) in our sample during the filing year. *Bkrpt firms* provides the number of firms that filed for bankruptcy in a given year. *Matched bkrpt firms* presents the subset of bankrupt firms, based on our matching procedure, that filed for bankruptcy in a given year. As an example, consider the year 1995. There were 31 firms that filed for bankruptcy in 1995. Of these 31 firms, 15 firms got picked by our matching procedure. This is captured in the *Matched bankrupt firms* column. Firms that filed for bankruptcy in years 1990, 1991 and 1992 are not part of the matched sample because our matching criteria relies on data from three years before (1987, 1988, 1989 respectively) whereas our data sample begins only in 1990.

Year of filing	Firm universe	Bkrpt firms	Matched bkrpt firms	Percentage
1990	1248	42	0	0%
1991	1592	31	0	0%
1992	1809	42	0	0%
1993	2232	24	6	25%
1994	2933	49	18	37%
1995	3336	31	15	48%
1996	3317	26	12	46%
1997	3346	105	55	52%
1998	3706	173	95	55%
1999	3977	150	74	49%
2000	4111	134	64	48%
2001	4309	150	84	56%
2002	4498	154	80	52%
2003	5048	124	70	56%
2004	5602	136	87	64%
2005	5868	66	34	52%
2006	6093	50	30	60%
2007	6246	27	19	70%
2008	7522	20	16	80%
2009	3565	29	18	62%
2010	3284	26	21	81%
2011	3168	26	24	92%
2012	2748	37	18	49%
2013	937	50	29	58%
Total		1702	868	

Table 2: **Summary Statistics**

This table presents descriptive statistics of the key variables used in the following analyses. Panel (a) provides summary statistics for the Indian sample. Panel (b) provides summary statistics for the U.S. sample.

(a) Indian sample

	Bankrupt firms			Full sample		
	N	Mean	Median	N	Mean	Median
Matching variables						
Log(Total assets)	17526	5.779	5.628	90495	6.063	5.858
Average ROA	17526	0.082	0.082	90495	0.114	0.115
Control variables						
Leverage	17526	0.746	0.524	90495	0.393	0.311
PPE	17526	0.439	0.419	90495	0.355	0.333
CHGSALE	17526	-0.134	0	90495	0.042	0.076
SALES	17526	0.817	0.674	90495	1.009	0.849
STD(CF)	15132	0.118	0.086	76152	0.111	0.083
Outcome variable						
ABACC	17526	-0.006	0.002	90495	0.005	0.004

(b) U.S. sample

	Bankrupt firms			Full sample		
	N	Mean	Median	N	Mean	Median
Matching variables						
Log(Total assets)	6402	6.543	6.418	137652	5.597	5.357
Average ROA	6402	0.097	0.104	137652	0.066	0.11
Control variables						
Leverage	6402	0.337	0.304	137652	0.195	0.131
PPE	6400	0.378	0.346	137622	0.33	0.25
CHGSALE	6402	0.068	0.039	137652	0.084	0.055
SALES	6402	1.178	1.024	137652	1.051	0.882
STD(CF)	5954	0.127	0.076	126535	0.134	0.074
Outcome variable						
ABACC	6402	-0.009	-0.008	137652	0.001	-0.001

Table 3: Comparison of treated and control samples

This table measures the effectiveness of the matching procedure by presenting descriptive statistics of bankrupt and non-bankrupt (control) firm-year observations that are matched 3 years before bankruptcy. The number of treated observations three years before bankruptcy is 868 and the corresponding number of control observations is 1201. The *Values* column shows the median values of key variables for each sample. The *p-values* column compares the medians of the two samples to test the effectiveness of the matching procedure. The p-values for the matching variables indicate that the difference in medians is not statistically different from zero. The column on *Distributions* performs a Kolmogorov-Smirnov test for equality of distributions. The last column reports the scaled difference statistic following Abadie and Imbens (2011):

$$T = \frac{X_1 - X_2}{\sqrt{S_1^2 + S_2^2}}$$

The policy variables are scaled by total assets. All variables are winsorized at 1st and 99th percentile.

	N		Values		p-values for comparison of		Scaled Difference
	Treated	Control	Treated	Control	Medians	Distributions	
Matching variables							
Log(Total assets)	868	1201	5.779	5.82	0.61	0.58	-0.018
Average ROA	868	1201	0.068	0.074	0.22	0.08	-0.081
Control variables							
PPE	868	1201	0.428	0.364	0.00	0.00	0.246
Leverage	868	1201	0.535	0.349	0.00	0.00	0.240
CHGSALE	868	1201	-0.041	0.043	0.00	0.00	-0.175
SALES	868	1201	0.592	0.74	0.00	0.00	-0.159
STD(CF)	744	997	0.084	0.087	0.51	0.93	-0.022
Abnormal accruals	868	1201	0.007	0.008	0.87	0.88	0.027

Table 4: Correlation table

This table presents the Pearson correlations for the variables used in the analysis. *ABACC* is the main dependent variable, *Log(TA)* and *ROA* are the main matching variables and our main control variables are *Leverage*, *PPE*, *CHGSALE* and *SALES*.

	Correlations						
	ABACC	Log(TA)	ROA	Leverage	PPE	CHGSALE	SALES
Log(TA)	0.00 (0.97)						
ROA	0.09 (0.00)	0.13 (0.00)					
Leverage	0.02 (0.00)	-0.20 (0.00)	-0.22 (0.00)				
PPE	-0.04 (0.00)	-0.02 (0.00)	-0.06 (0.00)	0.24 (0.00)			
CHGSALE	0.05 (0.00)	0.17 (0.00)	0.36 (0.00)	-0.23 (0.00)	-0.11 (0.00)		
SALES	0.01 (0.00)	-0.04 (0.00)	0.27 (0.00)	-0.18 (0.00)	-0.23 (0.00)	0.54 (0.00)	
STD(CF)	0.03 (0.00)	0.09 (0.00)	0.11 (0.00)	-0.01 (-0.033)	-0.12 (0.00)	0.16 (0.00)	0.18 (0.00)

Table 5: **Abnormal accruals around bankruptcy filing for Indian firms**

This table reports the results of regressions investigating:

$$y_{it} = \beta_0 + \sum_{s=-5}^{-4} \Gamma_s \text{Pre-Bankruptcy}(-s)_{it} + \sum_{s=-2}^0 \Gamma_s \text{Pre-Bankruptcy}(-s)_{it} + \sum_{s=1}^5 \Gamma_s \text{Post-Bankruptcy}(s)_{it} + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

We estimate this regression on all firm-year observations in our sample from 1990 to 2013. *Pre-(Post) bankruptcy* (T) refer to a dummy variable that turns on in year T . $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. In Column (1), the effect is restricted to the sample of treated and control firms, 5 years before and after bankruptcy. Column (2) shows coefficients from the regression on the full sample. The regression in Column (3) uses the full sample but restricted to those industries that have at least one bankruptcy event. Column (4) is restricted to the time period post-year 2000. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the firm level. Coefficients on FEs are suppressed for brevity. All variables are defined in Appendix.

	Abnormal accruals			
	(1)	(2)	(3)	(4)
Pre-bankruptcy (-5)	0.003 [0.277]	-0.004 [-0.475]	-0.004 [-0.496]	-0.002 [-0.175]
Pre-bankruptcy (-4)	-0.008 [-0.720]	-0.018** [-2.143]	-0.018** [-2.171]	-0.019 [-1.411]
Pre-bankruptcy (-2)	-0.027*** [-2.956]	-0.036*** [-5.722]	-0.036*** [-5.754]	-0.034*** [-3.631]
Pre-bankruptcy (-1)	-0.045*** [-4.339]	-0.058*** [-7.717]	-0.058*** [-7.738]	-0.052*** [-5.367]
Pre-bankruptcy (0)	-0.041*** [-4.347]	-0.047*** [-6.914]	-0.048*** [-6.931]	-0.049*** [-5.201]
Post-bankruptcy (1)	-0.017* [-1.823]	-0.022*** [-3.469]	-0.022*** [-3.488]	-0.023*** [-2.778]
Post-bankruptcy (2)	-0.002 [-0.160]	-0.012* [-1.907]	-0.012* [-1.922]	-0.012 [-1.446]
Post-bankruptcy (3)	0.009 [0.864]	-0.009 [-1.428]	-0.009 [-1.427]	-0.008 [-1.095]
Post-bankruptcy (4)	-0.006 [-0.460]	-0.021*** [-2.623]	-0.021*** [-2.617]	-0.016* [-1.806]
Post-bankruptcy (5)	0.005 [0.399]	-0.018** [-2.113]	-0.018** [-2.109]	-0.017** [-2.028]
Constant	0.053* [1.745]	-0.077*** [-3.447]	-0.075*** [-3.343]	-0.005 [-0.460]
Observations	12,599	62,072	59,763	45,900
R-squared	0.215	0.176	0.176	0.213
Controls	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Year FE	Yes	42	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 6: **Depreciation expense around bankruptcy filing for Indian firms**

This table reports the results of regressions investigating:

$$y_{it} = \beta_0 + \sum_{s=-5}^{-4} \Gamma_s \text{Pre-Bankruptcy}(-s)_{it} + \sum_{s=-2}^0 \Gamma_s \text{Pre-Bankruptcy}(-s)_{it} + \sum_{s=1}^5 \Gamma_s \text{Post-Bankruptcy}(s)_{it} + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

We estimate this regression on all firm-year observations in our sample from 1990 to 2013. *Pre-(Post) bankruptcy* (T) refer to a dummy variable that turns on in year T . $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. In Column (1), the effect is restricted to the sample of treated and control firms, 5 years before and after bankruptcy. Column (2) shows coefficients from the regression on the full sample. The regression in Column (3) uses the full sample but restricted to those industries that have at least one bankruptcy event. Column (4) is restricted to the time period post-year 2000. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the firm level. Coefficients on FEs are suppressed for brevity. All variables are defined in Appendix.

	Depreciation expense			
	(1)	(2)	(3)	(4)
Pre-bankruptcy (-5)	0.003 [0.684]	0.001 [0.522]	0.001 [0.534]	0.001 [0.338]
Pre-bankruptcy (-4)	0.004 [1.161]	0.003 [1.574]	0.003 [1.599]	0.005 [1.279]
Pre-bankruptcy (-2)	0.004 [1.530]	0.004* [1.666]	0.004* [1.700]	0.004 [1.144]
Pre-bankruptcy (-1)	0.009** [2.560]	0.010*** [3.677]	0.010*** [3.702]	0.008* [1.759]
Pre-bankruptcy (0)	0.004 [1.082]	0.007** [2.101]	0.007** [2.127]	0.005 [1.072]
Post-bankruptcy (1)	0.000 [0.062]	0.003 [1.032]	0.003 [1.050]	-0.000 [-0.020]
Post-bankruptcy (2)	0.004 [0.836]	0.006 [1.620]	0.006 [1.633]	0.004 [0.835]
Post-bankruptcy (3)	0.004 [0.679]	0.007* [1.710]	0.007* [1.714]	0.005 [1.128]
Post-bankruptcy (4)	0.006 [1.153]	0.005 [1.233]	0.005 [1.243]	0.004 [0.783]
Post-bankruptcy (5)	0.000 [0.010]	0.001 [0.286]	0.001 [0.289]	-0.000 [-0.089]
Constant	0.123*** [9.144]	0.112*** [18.680]	0.113*** [18.526]	0.154*** [21.059]
Observations	12,594	62,043	59,734	45,877
R-squared	0.630	0.650	0.640	0.697
Controls	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 7: **Abnormal accruals - Effect of creditors and group affiliation**

This table reports the results of regressions investigating

$$y_{it} = \beta_0 + \beta_1 \text{Pre-Bankruptcy}(-5,-4)_{it} + \beta_2 \text{Pre-Bankruptcy}(-2)_{it} + \beta_3 \text{Pre-bankruptcy}(-1) + \beta_4 \text{Pre-bankruptcy}(0) + \beta_5 \text{Post-bankruptcy}(>0) + \beta_6 Z_{it} + \beta_7 \text{Pre-Bankruptcy}(-1)_{it} \times Z_{it} + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

We estimate this regression for the period 1990 to 2013. *Pre-bankruptcy*(*T*) is a dummy variable that is one if the current year is *T* years before bankruptcy filing. *Post-bankruptcy* is a dummy that is one if the current year is one or more years after bankruptcy. *SARFAESI* is a dummy variable that is one if the current year is on or after 2002 (the year of SARFAESI implementation). $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. Column (1) refers to coefficients for the Group affiliated firms, Column (2) shows coefficients for the non-group firms. Column (3) is the difference (Group - Non-group). We interact all RHS variables with a dummy variable for *Group* and with $(1-\text{Group})$. All regressions are restricted to 5 years before and after bankruptcy filing. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the industry level. Coefficients on fixed effects are suppressed for brevity. All variables are defined in Appendix.

	Abnormal accruals		
	Group	Non-group	Diff
	(1)	(2)	(3)
Pre bankruptcy(-5,-4)	-0.011 [-0.955]	0.006 [0.477]	-0.017 [-1.10]
Pre bankruptcy(-2)	-0.026** [-2.032]	-0.025** [-2.121]	-0.001 [-0.08]
Pre bankruptcy(-1)	-0.045** [-2.274]	-0.059*** [-4.170]	0.014 [0.58]
Pre-bankruptcy (0)	-0.048*** [-3.649]	-0.037*** [-3.127]	-0.011 [-0.63]
Post-bankruptcy(>0)	-0.020 [-1.512]	0.001 [0.108]	-0.021 [-1.22]
SARFAESI	-0.104*** [-3.614]	-0.115*** [-3.901]	0.011 [1.34]
SARFAESI X Pre-bankruptcy(-1)	-0.003 [-0.147]	0.036** [2.065]	-0.039 [-1.54]
Observations		11,304	
R-squared		0.223	
F-test ($\beta_3 + \beta_7 = 0$)			
F statistic		1.94	
Prob >F		0.165	
Controls	Yes	Yes	
Size FE	Yes	Yes	
Year FE	Yes	Yes	
Firm FE	Yes	Yes	

Table 8: **Effect of accruals on post bankruptcy performance**

This table reports the results of regressions investigating:

$$y_{it}^{post} = \beta_0 + \beta_1 \text{Pre-bankruptcy accruals}_{it-1} + \gamma X_{it-1} + \delta_{industry} + \delta_t + \varepsilon_{it}$$

We estimate this regression from 1990 to 2013. All variables are winsorized at the 1st and 99th percentile. All variables are defined in the Appendix. All regressions include standard errors clustered at the industry level. For brevity, we suppress the coefficients on the fixed effects. *Pre-bankruptcy accruals* refers to pre-bankruptcy accruals in year T-1. The dependent variables are averaged over three years after BIFR filing (T+1 to T+3). $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage, Cash Flow. All regressions are restricted to the sample of bankrupt firms. The control variables are measured in the year before bankruptcy. All regressions include industry, year and size decile fixed effects.

	Post-bk. ROA			Post-bk. Cash Flow			Post-bk. Revenue		Diff (9)
	India	U.S.	Diff	India	U.S.	Diff	India	U.S.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Pre-bk. acc.	0.089*** [3.204]	-0.094 [-1.265]	0.183** [2.23]	0.021 [0.511]	-0.260*** [-3.562]	0.281*** [3.32]	0.625*** [5.011]	-0.307 [-0.739]	0.932** [2.07]
PPE	0.053** [2.174]	0.065 [1.425]		0.019 [0.652]	-0.033 [-0.692]		0.003 [0.031]	-0.263 [-1.199]	
CHGSALE	0.043*** [3.933]	-0.045 [-1.138]		0.007 [0.367]	-0.078*** [-3.296]		0.169*** [2.810]	0.268 [0.581]	
SALES	0.008 [1.262]	-0.007 [-0.538]		0.009 [0.688]	-0.015 [-0.889]		0.761*** [9.439]	0.666*** [11.943]	
STD(CF)	0.034 [0.708]	0.059 [1.383]		-0.100 [-1.545]	-0.298 [-1.583]		0.267 [1.258]	-0.691** [-2.642]	
Cash Flow	0.079*** [2.900]	0.132*** [3.474]		0.109** [2.302]	-0.072 [-0.775]		0.394*** [4.126]	-0.228* [-1.957]	
Leverage	-0.001 [-0.050]	-0.009 [-0.457]		-0.004 [-0.470]	0.003 [0.086]		-0.050 [-1.199]	0.008 [0.068]	
Size FE	Yes	Yes		Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Industry FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations						814			

Table 9: **Pre-bankruptcy Accruals and Announcement Returns**

This table studies stock market reaction to BIFR registration. We report differences in bankruptcy filing announcement returns between firms with high and low pre-bankruptcy accruals. The sample comprises 57 firms for which information on actual date of BIFR registration is available. We perform the announcement study for various event windows around the registration date as indicated in Columns (1) - (4). Thus *3-day* in Column (1) refers to the window T-1, T, and T+1 where T is the registration date. Similarly, *5-day* in Column (2) refers to the window from T-2 to T+2. We provide estimates of *Announcement Returns* (in percentage) which capture the average difference between realized stock returns and predicted stock returns within the event window. Predicted stock returns are estimated over an estimation window of 30 days in the pre-event period using a regression framework with market returns as the main explanatory factor. Firms are classified under High (Low) pre-bankruptcy accruals if the average abnormal accruals in a five year pre-bankruptcy period is above (below) median.

	Obs.	Announcement Returns (%)			
		3-day (1)	5-day (2)	7-day (3)	10-day (4)
All firms	57	-0.47	-0.079	-0.202	-0.177
High pre-bankruptcy accruals	28	-0.004	0.504	0.537	0.462
Low pre-bankruptcy accruals	29	-0.92	-0.641	-0.915	-0.815
Difference		0.916*	1.145**	1.452**	1.277**
T-statistic		1.35	1.77	2.34	2.16

Table 10: **Abnormal accruals around bankruptcy filing - Comparison of Indian and U.S. firms**

This table reports the results of regressions investigating

$$y_{it} = \beta_0 + \beta_1 \text{Pre-Bankruptcy}(-5,-4)_{it} + \beta_2 \text{Pre-Bankruptcy}(-2)_{it} \\ + \beta_3 \text{Pre-bankruptcy}(-1) + \beta_4 \text{Pre bankruptcy}(0) \\ + \beta_5 \text{Postbankruptcy}(>0) + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

We estimate this regression on a combined sample of Indian and U.S. firms for the period 1990 to 2013. *Pre-bankruptcy*(*T*) is a dummy variable that is one if the current year is *T* years before bankruptcy filing. *Post-bankruptcy* is a dummy that is one if the current year is one or more years after bankruptcy. $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. Column (1) refers to coefficients for the Indian sample, Column (2) shows coefficients for the U.S. sample. Column (3) is the difference (India - U.S.). We use a combined sample of Indian and U.S. firms and interact all RHS variables with a dummy variable for *India* and with (*1-India*). All regressions are restricted to 5 years before and after bankruptcy filing. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the industry level. Coefficients on fixed effects are suppressed for brevity. All variables are defined in Appendix.

	Abnormal accruals		
	India	U.S.	Diff
	(1)	(2)	(3)
Pre bankruptcy(-5,-4)	0.000 [0.004]	0.000 [0.033]	0.000 [-0.02]
Pre bankruptcy(-2)	-0.028*** [-3.155]	-0.005 [-0.601]	-0.023* [-1.93]
Pre bankruptcy(-1)	-0.048*** [-4.840]	-0.025*** [-2.946]	-0.023* [-1.77]
Pre-bankruptcy (0)	-0.047*** [-5.065]	0.026* [1.716]	-0.073*** [-4.13]
Post-bankruptcy(>0)	-0.013* [-1.902]	-0.000 [-0.025]	-0.013 [-1.05]
Observations		21,816	
R-squared		0.214	
Controls	Yes	Yes	
Size FE	Yes	Yes	
Year FE	Yes	Yes	
Firm FE	Yes	Yes	

Table 11: Cash flows around bankruptcy filing - Comparison of Indian and U.S. firms

This table reports the results of regressions investigating

$$y_{it} = \beta_0 + \beta_1 \text{Pre-Bankruptcy}(-5,-4)_{it} + \beta_2 \text{Pre-Bankruptcy}(-2)_{it} + \beta_3 \text{Pre-bankruptcy}(-1) + \beta_4 \text{Pre bankruptcy}(0) + \beta_5 \text{Postbankruptcy}(> 0) + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

We estimate this regression on a combined sample of Indian and U.S. firms for the period 1990 to 2013. *Pre-bankruptcy*(*T*) is a dummy variable that is one if the current year is *T* years before bankruptcy filing. *Post-bankruptcy* is a dummy that is one if the current year is one or more years after bankruptcy. $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. Column (1) refers to coefficients for the Indian sample, Column (2) shows coefficients for the U.S. sample. Column (3) is the difference (India - U.S.). We use a combined sample of Indian and U.S. firms and interact all RHS variables with a dummy variable for *India* and with (*1-India*). All regressions are restricted to 5 years before and after bankruptcy filing. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the industry level. Coefficients on fixed effects are suppressed for brevity. All variables are defined in Appendix..

	Cash flow		
	India	U.S.	Diff
	(1)	(2)	(3)
Pre bankruptcy(-5,-4)	0.015 [1.578]	0.019* [1.947]	-0.004 [-0.29]
Pre bankruptcy(-2)	-0.008 [-0.751]	-0.029** [-2.539]	0.021 [1.46]
Pre bankruptcy(-1)	-0.044*** [-3.464]	-0.094*** [-6.721]	0.05*** [2.72]
Pre-bankruptcy (0)	-0.011 [-1.105]	-0.138*** [-4.182]	0.127*** [3.70]
Post-bankruptcy(>0)	0.020* [1.841]	-0.018 [-0.961]	0.038* [1.84]
Observations		21,816	
R-squared		0.307	
Controls	Yes	Yes	
Size FE	Yes	Yes	
Year FE	Yes	Yes	
Firm FE	Yes	Yes	

Table 12: Depreciation expense around bankruptcy filing - Comparison of Indian and U.S. firms

This table reports the results of regressions investigating

$$y_{it} = \beta_0 + \beta_1 \text{Pre-Bankruptcy}(-5,-4)_{it} + \beta_2 \text{Pre-Bankruptcy}(-2)_{it} + \beta_3 \text{Pre-bankruptcy}(-1) + \beta_4 \text{Pre bankruptcy}(0) + \beta_5 \text{Postbankruptcy}(> 0) + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

We estimate this regression on a combined sample of Indian and U.S. firms for the period 1990 to 2013. *Pre-bankruptcy*(*T*) is a dummy variable that is one if the current year is *T* years before bankruptcy filing. *Post-bankruptcy* is a dummy that is one if the current year is one or more years after bankruptcy. $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. Column (1) refers to coefficients for the Indian sample, Column (2) shows coefficients for the U.S. sample. Column (3) is the difference (India - U.S.). We use a combined sample of Indian and U.S. firms and interact all RHS variables with a dummy variable for *India* and with (*1-India*). All regressions are restricted to 5 years before and after bankruptcy filing. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the industry level. Coefficients on fixed effects are suppressed for brevity. All variables are defined in Appendix..

	Depreciation Expense		
	India	U.S.	Diff
	(1)	(2)	(3)
Pre bankruptcy(-5,-4)	0.002 [0.677]	-0.001 [-0.671]	0.003 [0.89]
Pre bankruptcy(-2)	0.007*** [2.705]	-0.001 [-0.609]	0.008*** [2.59]
Pre bankruptcy(-1)	0.014*** [4.181]	-0.006** [-2.524]	0.02*** [4.90]
Pre-bankruptcy (0)	0.011*** [3.086]	-0.011*** [-3.923]	0.021*** [5.15]
Post-bankruptcy(>0)	0.012*** [3.327]	-0.009** [-2.345]	0.021*** [4.20]
Observations		21,804	
R-squared		0.694	
Controls	Yes	Yes	
Size FE	Yes	Yes	
Year FE	Yes	Yes	
Firm FE	Yes	Yes	

Table 13: **Placebo test of financial distress (drop in cash flow)**

This table reports the results of regressions investigating:

$$y_{it} = \beta_0 + \sum_{s=-5}^{-4} \Gamma_s \text{Pre-CF-event}(-s)_{it} + \sum_{s=-2}^0 \Gamma_s \text{Pre-CF-event}(-s)_{it} + \sum_{s=1}^5 \Gamma_s \text{Post-CF-event}(s)_{it} + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

This table tests the behavior of abnormal accruals around events with a significant drop (50% YoY decrease in T-1 and T) in the cash flow variable. We estimate this regression from 1990 to 2013 after removing all BIFR firms. *Pre-(Post) CF event (T)* refer to a dummy variable that turns on in year T. $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. In Column (1), the effect is restricted to the sample of treated and control firms, 5 years before and after event. Column (2) shows coefficients from the regression on the full sample. Column (3) is on the full sample but restricted to those industries that have at least one negative cash flow event. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the firm level.

	Abnormal Accruals		
	(1)	(2)	(3)
Pre-CF event (-5)	0.010 [1.097]	0.014** [2.109]	0.014** [2.110]
Pre-CF event (-4)	0.006 [0.920]	0.010* [1.734]	0.010* [1.734]
Pre-CF event (-2)	-0.011** [-2.057]	-0.001 [-0.177]	-0.001 [-0.176]
Pre-CF event (-1)	0.017** [2.429]	0.026*** [4.776]	0.026*** [4.777]
Post-CF event (0)	-0.002 [-0.320]	0.008** [2.162]	0.008** [2.161]
Post-CF event (1)	-0.014** [-2.207]	-0.000 [-0.134]	-0.000 [-0.135]
Post-CF event (2)	-0.013* [-1.905]	-0.001 [-0.335]	-0.001 [-0.335]
Post-CF event (3)	-0.018** [-2.397]	-0.006 [-1.499]	-0.006 [-1.499]
Post-CF event (4)	-0.015* [-1.933]	-0.003 [-1.020]	-0.003 [-1.019]
Post-CF event (5)	-0.014* [-1.724]	-0.001 [-0.241]	-0.001 [-0.240]
Constant	0.008 [0.827]	0.008 [0.854]	0.009 [0.862]
Observations	28,832	49,644	49,588
R-squared	0.225	0.172	0.172
Controls	Yes	Yes	Yes
Size FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 14: **Placebo test for non-industrial firms**

This table reports the results of regressions investigating:

$$y_{it} = \beta_0 + \sum_{s=-5}^{-4} \Gamma_s \text{Pre-NN-event}(-s)_{it} + \sum_{s=-2}^0 \Gamma_s \text{Pre-NN-event}(-s)_{it} + \sum_{s=1}^5 \Gamma_s \text{Post-NN-event}(s)_{it} + \gamma X_{it-1} + \delta_i + \delta_t + \varepsilon_{it}$$

This table tests the behavior of abnormal accruals around negative networth events for non-industrial firms (i.e. firms outside the purview of BIFR). We estimate this regression from 1990 to 2013 on all (non-BIFR) firms in services industries (for e.g. Health Services, Courier Services, Transport Services etc). We identify T as the negative networth event year (*NN event*) defined as the year when net worth switches from positive to negative. Firms that do not experience a negative net worth event form part of the control sample. *Pre-(Post) NN event (X)* refer to a dummy variable that turns on X years before (or after) year T. $X_{i,t-1}$ refers to the control variables: PPE, Sales, Δ Sales, Std(CFO), Leverage. All variables are winsorized at the 1st and 99th percentile. Regressions includes firm FE, size decile FE and year FE. Robust standard errors are clustered at the firm level.

	Abnormal Accruals
Pre-NN event (-5)	-0.005 [-0.100]
Pre-NN event (-4)	-0.014 [-0.267]
Pre-NN event (-2)	0.008 [0.259]
Pre-NN event (-1)	-0.015 [-0.549]
Post-NN event (0)	0.009 [0.338]
Post-NN event (1)	-0.012 [-0.465]
Post-NN event (2)	0.023 [0.952]
Post-NN event (3)	-0.035* [-1.732]
Post-NN event (4)	-0.024 [-1.144]
Post-NN event (5)	0.011 [0.402]
Constant	0.008 [0.827]
Observations	2,044
R-squared	0.244
Controls	Yes
Size FE	Yes
Firm FE	Yes
Year FE	Yes

Table 15: Caliper matching and Rosenbaum (2002) bounds

This table reports sensitivity analysis following the Rosenbaum (2002) procedure. The main dependent variable is abnormal accruals in the year before bankruptcy filing. Treatment refers to the declaration of bankruptcy by a firm. The treatment effect is the decrease in abnormal accruals just before bankruptcy. The table documents the extent of hidden bias required to overturn the conclusion of the average treatment effect. We use propensity scores to predict the probability of treatment assignment based on observable covariates. We use a caliper size of 0.25 and our distance metric is the propensity score. The table provides an estimate of ATT. The last column estimates the extent of hidden bias required to alter the conclusions of our study.

Variable	Average treatment effect on treated	Number of matched pairs	Gamma
Abnormal Accruals	-0.061***	640	1.8
Covariates			
ROA, PPE, CHGSALE, Sales, STD(CF), Cash Flow, Leverage			

Figure 1: Abnormal accruals before and after bankruptcy for treated and control firms

This figure presents the coefficients from a fully saturated model with separate dummy variables for the treated and control firms for the time period relative to the year of bankruptcy. The excluded category is three years before bankruptcy, which is the year we do the matching in. Thus the data point corresponding to year “t” can be interpreted as the difference in *Abnormal accruals* in year “t” relative to 3 years before bankruptcy. The red line represents the values for the bankrupt (treated) firms while the blue line represents the value for the control firms.

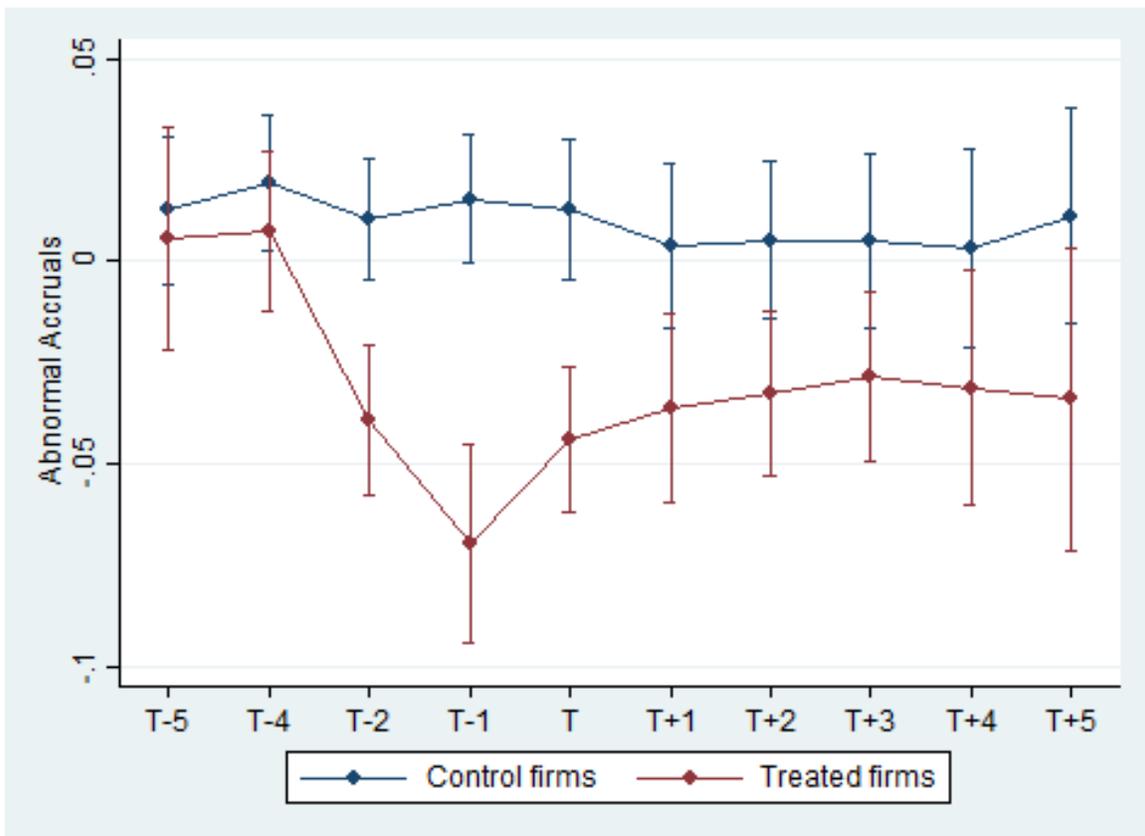


Figure 2: Placebo test - Abnormal accruals around distress (negative cash flow) events

This figure presents the coefficients from a fully saturated model with separate dummy variables for the treated and control firms for the time period relative to the year of the negative cash flow event. The excluded category is three years before the event, which is the year we do the matching in. Thus the data point corresponding to year “t” can be interpreted as the difference in *Abnormal accruals* in year “t” relative to 3 years before the negative cash flow event. The red line represents the values for the treated firms while the blue line represents the value for the control firms.

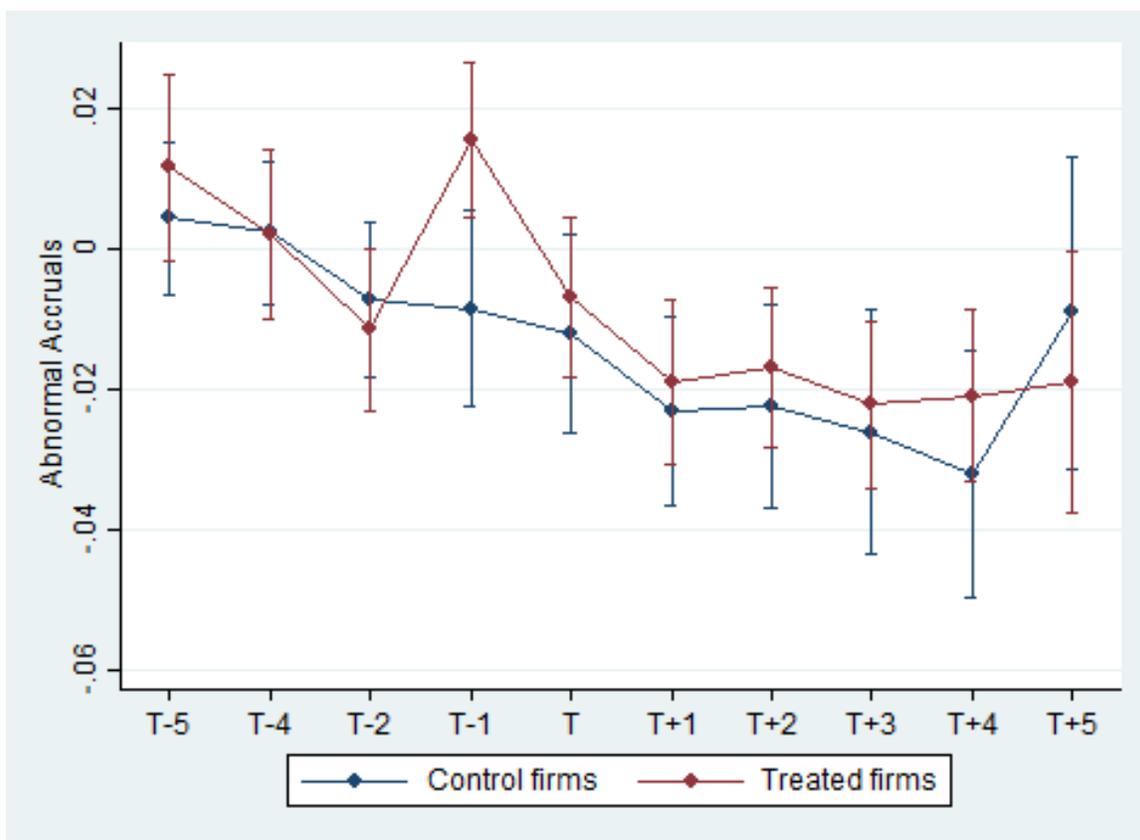
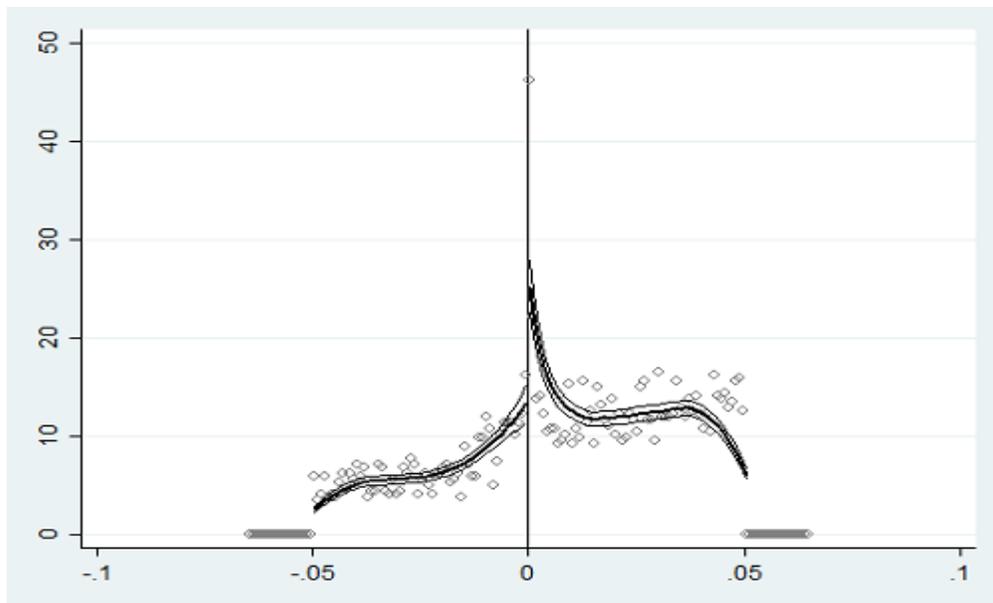
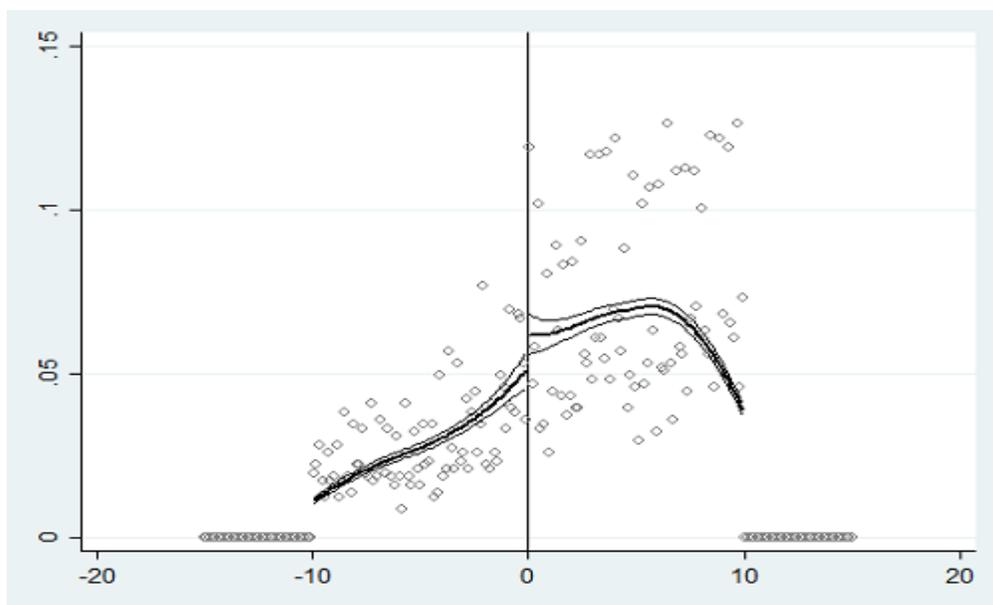


Figure 3: Net worth discontinuity

We plot the distribution of net worth values in our sample in Panel (a) and Panel (b). In Panel (a) we plot the density of firm's net worth scaled by total assets using the DCDensity procedure developed in McCrary [2008]. We plot the empirical density along with the 95% confidence interval and test for a discontinuity at zero. We focus on a small range (-0.05 to +0.05) around zero. The bin size (0.0008) is the default bin size estimated by the DCDensity function. The discontinuity estimate (log difference in height) is 0.665. In Panel (b), we use the reported value of network (in INR million) and repeat our density test. Here, we estimate a discontinuity (log difference in height) of 0.186. Note that the DCDensity procedure normalizes both X- and Y-axes so that the area under the curve is 1.



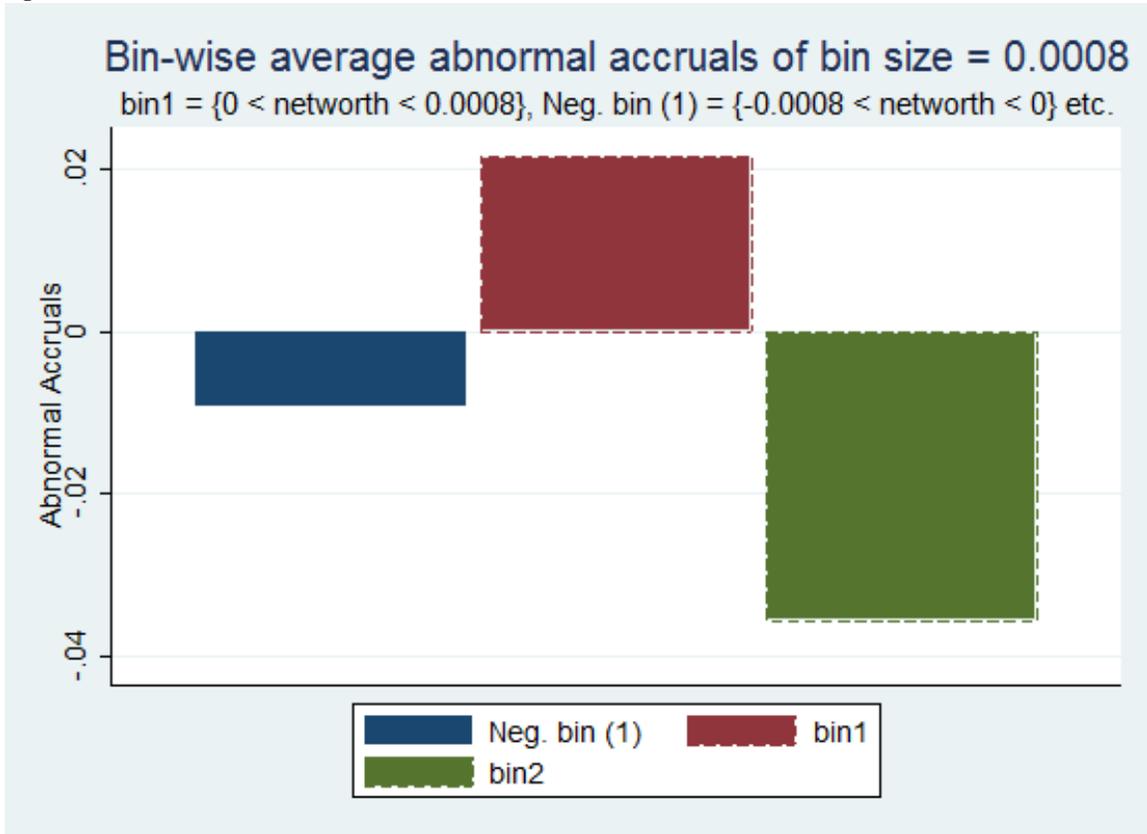
(a) Scaled Net worth density plot (net worth over total assets)



(b) Net worth density plot (in INRmn)

Figure 4: Abnormal accruals and net worth

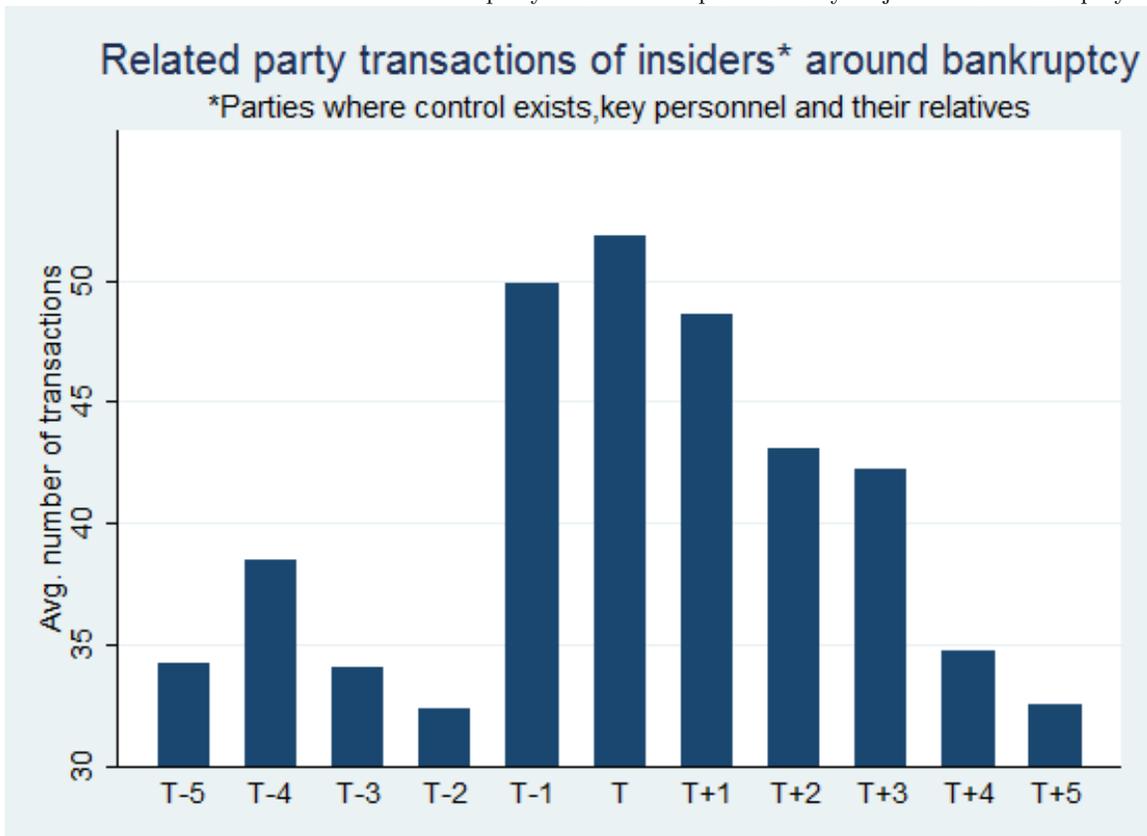
We plot the distribution of average abnormal accruals around net worth zero values. Figure shows the bin-wise average of abnormal accruals when the net worth variable (as a fraction of total assets) varies around zero. The average abnormal accruals becomes positive in the bin closest to zero and is statistically significant.



Two sample unpaired t-test			
Variable	Observations	Mean	Std. Err.
Positive bin 1	43	0.0099	0.017
Positive bin 2	39	-0.0351	0.020
Difference		0.045**	0.026
T-statistic		1.74	
P-value		0.0428	

Figure 5: Related party transactions around bankruptcy

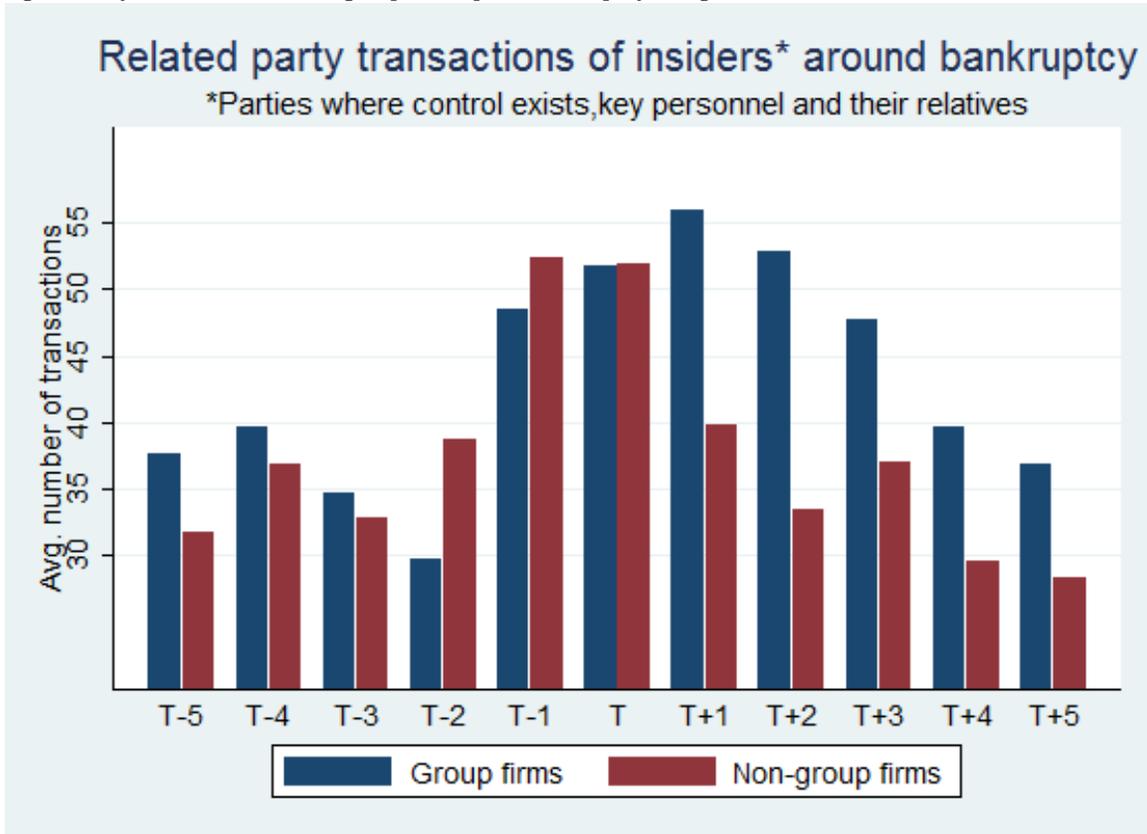
We plot the distribution of related party transactions around bankruptcy. Figure shows the distribution of average number of transactions for insiders defined as parties where control exists, key personnel or their relatives. We see that the number of related party transactions spikes in the year just before bankruptcy.



Two sample unpaired t-test			
Variable	Observations	Mean	Std. Err.
T-2	124	32.3	3.89
T-1	175	49.92	5.07
Difference		-17.61***	6.85
T-statistic		-2.57	
P-value		0.005	

Figure 6: Related party transactions between group and non-group firms

We plot the distribution of related party between group and non-group firms around bankruptcy. Figure shows the distribution of average number of transactions for insiders defined as parties where control exists, key personnel or their relatives. We see that the average number of transactions for group firms is significantly different from non-group firms post bankruptcy filing.



T+1				T+2			
Variable	Observations	Mean	Std. Err.	Variable	Observations	Mean	Std. Err.
Group	107	55.9	7.35	Group	111	52.83	8.11
Non-group	89	39.9	4.91	Non-group	113	33.53	3.61
Difference		16.0**	9.22	Difference		19.30**	8.82
T-statistic		1.74		T-statistic		2.19	
P-value		0.042		P-value		0.015	