Mandatory CSR Expenditure and Stock Market Liquidity

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ABSTRACT

We investigate the nexus between corporate social responsibility (CSR) and firms' stock market liquidity. Using actual firm-level CSR expenditure data and a quasi-natural experiment setup of a mandated CSR regulation in India, we find that firms complying with the mandate experience significantly higher stock market liquidity, relative to non-CSR firms in the post-CSR mandate period. This effect seems to be more pronounced among CSR firms not affiliated to business groups, with concentrated promoter ownership, with low institutional ownership, with foreign sales and having operations in multiple locations. Further, we find that firms spending more on education and healthcare projects as part of their mandatory CSR engagement have higher stock market liquidity. Our results are in line with the conjecture that mandatory CSR regulation could lead to reduced information asymmetry and improved social and reputational capital, and thus improve the stock market liquidity of CSR firms. Finally, we show that mandated CSR firms, having superior stock market liquidity, obtain higher market valuations in the long run.

JEL Codes: G12; G14; G38; M14

Key Words: CSR; Stock market liquidity; Mandatory CSR law; Social capital; ESG

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1. Introduction

In recent years, the organizational philosophy of conducting business has altered from being only "investor-oriented", where the sole purpose of firms is to operate as profit-generating bodies, to becoming more "stakeholder-oriented", where companies are willingly devoting significant amounts of capital and resources for the overall welfare of non-equity stakeholders (Kitzmueller and Shimshack, 2012). In fact, administrative bodies in several countries have initiated enacting mandatory corporate social responsibility (CSR) related protocols (Chen et al., 2018; Grewal et al., 2019; Manchiraju and Rajgopal, 2017). In this study, we investigate how such mandatory engagement and reporting on CSR activities affect stock market liquidity, one of the crucial parameters of firms' financial performance.

Extant literature suggests that a firm's higher stock market liquidity is associated with lower cost of capital (Amihud and Mendelson, 1986; Diamond and Verrecchia, 1991), superior stock prices, and firm value (Fang et al., 2009; Holmström and Tirole, 1993), and higher institutional and foreign ownership (Ferreira and Matos, 2008; Gompers and Metrick, 2001). As a result, stock market liquidity is highly associated with firms' financial development and growth (Guiso et al., 2008, 2004). However, how a firm's engagement in CSR impacts its stock market liquidity remains an empirical issue. There is a growing focus in the literature on how the CSR activities of corporations are influenced through mandatory CSR regulations. Where governments use these interventions as instruments to raise social awareness and give CSR a proper policy priority (Cominetti and Seele, 2016). A broad stream of literature examines and provides ample empirical evidence that CSR may help reduce information asymmetry (Cui et al., 2018; Orlitzky et al., 2003) and increase social and reputational capital (Fombrun and

Shanley, 1990; Lins et al., 2017), both of which can positively affect stock liquidity in financial markets.

Furthermore, institutional theory suggests that the CSR behavior of firms is driven by the process of coercive isomorphism wherein mandatory CSR regulations improve the information environment and, consequently, generate greater confidence within the investor community and, in turn, drive up stock market liquidity (Hess, 2007). Additionally, the recent growth in environment, social, and governance (ESG) awareness among asset managers, analysts, and investors is also driving the demand for stocks of firms engaged in CSR activities, which should also therefore positively influence stock market liquidity (Amel-Zadeh and Serafeim, 2018; Hartzmark and Sussman, 2019; Ioannou and Serafeim, 2015).

The Indian market provides an appropriate setting to investigate our main research question as to whether mandatory CSR expenditure improves the stock market liquidity of CSR firms. This is because of two reasons; First, India enacted Section 135 (referred to as S-135 hereon) as part of the Companies Act 2013 which mandates firms satisfying certain size thresholds to engage in prescribed CSR activities by spending at least 2% of net profits (Dharmapala and Khanna, 2018; Manchiraju and Rajgopal, 2017).[1] Since S-135 exogenously determines treated (affected by S-135) and control groups (unaffected by S-135) firms, we exploit S-135 as a regulatory exogenous shock in our empirical analysis. Second, as per the World Bank database, for our sample period of study (2012-2017), the average total market capitalization of the Indian equity market was USD 1.73 trillion and with an average annual trading volume of USD 789.41 billion. In comparison, during the same sample period the market capitalization (trading volume) of the USA and China was USD 25.59 trillion (USD

[1] S-135 is a unique CSR regulation as it prescribes the firm a minimum expenditure on CSR as well as to disclose all CSR related information. For details see https://www.india-briefing.com/news/corporate-social-responsibility-india-5511.

38.41 trillion) and USD 6.31 trillion (USD 15.17 trillion), respectively. In terms of listed companies, during the sample period, an average of 5549 companies was listed in Indian stock exchanges, while there were 4283 listed companies in the USA and 2826 companies listed in China. The World Bank data shows that India figures consistently among the 10 largest equity markets in the world.

To causally identify the effect of CSR on firms' stock market liquidity, we adopt the propensity scored matched difference-in-differences (PSM-DiD) quasi-natural experiment with S-135 as the exogenous regulatory shock. We use a sample of publicly-traded non-financial firms in India for the sample period 2012-2017 and employ four widely used low-frequency stock market liquidity measures, namely *Amihud* illiquidity ratio measure of Amihud (2002), *Zeros* measure of Lesmond et al. (1999), high-low (*HL*) spread measure of Corwin and Schultz (2012), and *FHT* measure of Fong et al. (2017) in our empirical investigation. We find that, in the post-S-135 period, mandated CSR firms experienced significantly higher stock market liquidity, compared to non-CSR firms. In economic terms, we find that treated firms had a lower price impact in the range of 20.56% to 21.89%, relative to control firms in the post-CSR mandate period. In terms of spread proxies, the results indicate that compared to non-CSR firms, CSR firms experienced lower bid-ask spreads in the range of 9.61% to 32.56% in the post-S-135 period.

Our findings are robust to a series of robustness tests that include alternative definitions of treated and control groups, alternative stock market liquidity measures, and placebo tests. We also support our main findings of the causal effect using an alternative quasi-experiment technique of multivariate regression discontinuity design (MRDD). Additionally, we conduct cross-sectional analyses which reveal that mandated CSR firms not affiliated to business groups, with concentrated promoter ownership, having low institutional ownership, with foreign revenues, and having operations in multiple locations have higher stock market liquidity in the post-S-135 period. Together our empirical analysis supports our conjecture that mandated CSR firms experience higher stock market liquidity, relative to non-CSR firms in the post-CSR mandate period.

Extending the study, we utilize a novel dataset of the firm's actual expenditures on different CSR projects (sectors) and examine how firm-level expending in heterogenous CSR activities is associated with stock market liquidity.[2] In line with our main results, we find that the aggregate firm-level CSR expenditure is positively associated with stock market liquidity. Further analysis reveals that CSR expenditures allocated in education and healthcare projects primarily attribute to the higher stock market liquidity when compared to other projects such as social justice and the environment. We conjecture that firms spending on CSR projects that could help satisfy basic human needs such as education and healthcare may obtain higher stock market liquidity through the acquisition of higher social and reputation capital.

Finally, despite the economic arguments and empirical evidence that mandatory CSR regulations may reduce complying firms' market value in the short-run (Grewal et al., 2019; Manchiraju and Rajgopal, 2017), we show that in the long-run mandated CSR firms, obtaining higher stock market liquidity, tend to have higher market-based valuations.[3] Our mediation analysis confirms that CSR mandates are value-relevant for firms in the long run (Ioannou and Serafeim, 2017) and that stock market liquidity acts as a channel through which mandatory CSR engagement increases firm value (Fang et al., 2009; Holmström and Tirole, 1993).

[2] In their review of the CSR literature in the international context, Pisani et al. (2017) recommend exploiting various novel CSR related data sources (other than voluntary disclosures or ESG metrics) in different settings (i.e., developed and emerging markets) to exploit new dimensions and avenues in the field of CSR research.

[3] Chen et al. (2018) study the effect of a CSR reporting mandate in China and document a negative relationship between CSR reporting and performance in post-regulatory period. Our study differs from theirs in several aspects. First, the Chinese CSR mandate only requires firms to disclose CSR activities whereas S-135 requires firms to both report and spend on CSR activities. Further, we exploit S-135 and a unique CSR expenditure data to study the impact of CSR on stock market liquidity. Finally, we identify stock market liquidity as a possible channel through which mandated CSR improves CSR firms market value in the long run.

Our study makes several contributions to the literature. While the literature has predominantly focused on voluntary CSR (Bénabou and Tirole, 2010; Garriga and Melé, 2004; Hemingway and Maclagan, 2004; Servaes and Tamayo, 2017), our study contributes to the small but growing area of the mandatory CSR literature (Cominetti and Seele, 2016; Grewal et al., 2019; Manchiraju and Rajgopal, 2017). First, we add to the debate on how CSR is associated with information asymmetry and ultimately stock market liquidity. Numerous studies indicate that CSR is a manifestation of managerial agency issues that leads to higher information asymmetry, which could lead to lower stock market liquidity (Bénabou and Tirole, 2010; Hemingway and Maclagan, 2004). In contrast, we conjecture and show that mandatory CSR engagement could alleviate information asymmetry (reduced adverse selection costs, private information-seeking costs, and monitoring costs of traders) through better transparency and disclosure, leading to superior stock market liquidity (Diamond and Verrecchia, 1991; Kurlat, 2018).

Second, we contribute to the literature on the positive impacts of CSR-induced social and reputational capital (Fombrun and Shanley, 1990; Servaes and Tamayo, 2017). We conjecture and show that mandatory CSR regulation-induced expenditures help firms to obtain higher social and reputation capital which, in turn, lead to higher stock market liquidity (Blau, 2017; Guiso et al., 2008). Third, we add to the CSR and firm performance debate. Contrary to the studies showing negative short-term market reactions to mandatory CSR (Grewal et al., 2019; Manchiraju and Rajgopal, 2017), we show that mandatory CSR engagement is value-relevant and that the mandated CSR induced superior stock market liquidity acts as a channel through which CSR firms obtain higher market value in the long run.

Finally, recent studies investigating the relationship between CSR and stock market liquidity heavily rely on ESG indices to measure CSR performance (Chang et al., 2018; Egginton and McBrayer, 2019). ESG indices tend to be inconsistent across different industries and years and therefore may be susceptible to endogeneity and identification issues (Atanasov and Black, 2016; Park and Ravenel, 2013). For instance, Egginton and McBrayer (2019) document that firms' voluntary CSR activities are positively associated with stock market liquidity. On the contrary, Chang et al. (2018) show a negative association between stock market liquidity and firms' voluntary CSR activities.[4] These studies, using ESG indices, suggest tension in the debate on the relationship between CSR and stock market liquidity under voluntary CSR regimes. In contrast, using a shock-based quasi-experiment approach and actual CSR expenditure data, we provide credible evidence that mandatory CSR activities are positively associated with stock market liquidity. To the best of our knowledge, this is the first paper to show such a causal association between mandatory CSR engagement and stock market liquidity using actual firm-level CSR expenditure data instead of an index.[5]

The rest of the paper is organized as follows. Section 2 provides a brief description of the background of S-135. Section 3 provides a review of related literature and develops hypotheses. Section 4 describes the data and variables. Section 5 illustrates the empirical strategy. Section 6 reports all empirical findings. Finally, Section 7 concludes the paper.

2. Background of Section 135

Regulators across the world are mandating CSR disclosures due to the growing pressures from various stakeholders to move towards sustainability. For instance, before 2011, countries such as Denmark, South Africa, China, and Malaysia have mandated the firms to make

[4] For the US market, Chang et al. (2018) find that higher stock market liquidity leads to lower firm level voluntary CSR activities. On the contrary, in an emerging market setup, we show mandatory CSR law that requires firms to engage and expend in CSR activities lead to greater stock market liquidity. We conjecture that such a positive effect on stock market liquidity of CSR firms could be contributed towards the mandatory CSR induced lower information asymmetry, reduced agency problems, higher social and reputational capital, and greater stock market participation by institutional and foreign investors. Our findings are particularly important for emerging markets where stock selection is particularly challenging due to higher information asymmetry, agency problems, and transaction costs (Bekaert and Harvey, 2003).

[5] We conjecture that actual CSR expenditure data capture firms' CSR performance better than ESG indices as such ESG ratings are subjected to different rater's views of the firms and tend to be biased (Berg et al., 2020).

sustainability-related disclosures, and after 2012 Hong Kong, Brazil, Finland, and Sweden followed suit with similar regulations (Ioannou and Serafeim, 2017). In line with these countries and the UN sustainable goals agenda, and to provide a framework to encourage companies to meaningfully contribute to communities, the Government of India introduced Section 135 (S-135) in the Company Act 2013 (Dharmapala and Khanna, 2018).

The Company Bill (hereafter named Bill) introduced in the Indian Parliament in 2009, initially had no clause on CSR. However, following the report submitted by the finance standing committee a notion of mandatory CSR was introduced in the Bill in 2010. Following intensive objections, this was declared as a voluntary requirement. The mandatory clause was reintroduced in the Bill in 2012 and the Bill was signed into law as ‘The Companies Act 2013’. The S-135 came into effect from April 1, 2014, that is it became applicable in the fiscal year ending March 2015 (FY 2015).

The S-135 mandates qualifying firms to set up a CSR committee of three directors of which one should be an independent director, and to disclose the conformation of the committee. The CSR committee must formulate the firm’s CSR policy for the recommended CSR activities and the board should approve and publicize the CSR policy. S-135 also mandates that the board ensures that the firm spends at least 2% of the previous three years' net profit or explain non-compliance. The violation of mandatory provisions unavoidable through explanation would result in severe penalties that will include the firm and its responsible personnel paying a fine of INR 10,000 on the first day, and an additional INR 1,000 for each of the following days after the defilement until it is resolved.

The compliance under the S-135 for a firm depends on certain thresholds set out in the clause. The mandatory provisions of S-135 apply to all public and private firms conducting operations inside India (including foreign-owned firms) that reach at least one of the following three thresholds in any fiscal year has (i) a net worth of Indian Rupees (INR) 5 billion (about USD 67 million) or more, (ii) sales of INR 10 billion (about USD 133 million) or more, or (iii) a net profit of INR 50 million (about USD 0.67 million) or more. Once a firm qualifies under S-135 to comply with the provisions of the clause, these firms must spend 2% of their average net profits of the last three years on CSR activities (Dharmapala and Khanna, 2018; Manchiraju and Rajgopal, 2017). India's S-135 is the first regulation in the world that not only prescribes but also mandates firms a minimum expenditure on CSR activities.

As per the directive of the Indian Ministry of Corporate Affairs, only certain activities are eligible under the 'CSR activity' of clause S-135 for being recognized as CSR expenditure. These include expenditures incurred in areas of eradicating extreme hunger and poverty, promotion of education, promoting gender equality and empowering women, reducing child mortality and improving maternal health, combating HIV, AIDS, malaria, and other contagious and fatal diseases, ensuring environmental sustainability, social business projects, contribution to the prime minister's national relief fund or any other fund founded by the Central Government or the State Governments for socio-economic development and relief, and funds for the welfare of the scheduled castes, the scheduled tribes, other backward classes, minorities and women, and such other matters as may be prescribed from time to time.

3. Related literature and hypotheses development

Extent CSR literature predominantly concentrates on voluntary CSR practices of corporations. While some studies focus on CSR activities as an instrument to achieve a competitive advantage (Garriga and Melé, 2004; Servaes and Tamayo, 2017), others discuss agency issues related to voluntary CSR (Bénabou and Tirole, 2010; Hemingway and Maclagan, 2004). In recent years, however, there is a growing focus on how the government and other regulatory institutions are influencing the firms' CSR activities through mandatory CSR regulations and interventions. Using such interventions as instruments, the government aims at raising social awareness and giving CSR a proper policy priority (Cominetti and Seele, 2016). The S-135 of the Indian Companies Act 2013 falls under this mandatory CSR regulation and questions the established idea of CSR as merely a managerial tool of self-regulation (Gatti et al., 2019). Given this transition towards mandatory CSR literature, we theorize how mandatory CSR activities reduce information asymmetry, improve social capital, and in turn, increase stock market liquidity. In this regard, we discuss our views below.

Information Asymmetry: The seminal work of Akerlof (1970) contends agency issues can induce information asymmetry that can diminish the volume of trades in capital markets. In other words, information asymmetry is key in understanding a firm's stock market liquidity wherein firms with poor (better) disclosure and transparency should suffer from a lower (higher) level of stock market liquidity (Diamond and Verrecchia, 1991; Kurlat, 2018). Information asymmetry suggests that traders with more information impose adverse selection costs on those with less information (Glosten and Milgrom, 1985; Kyle, 1985). Further, when faced with changes in such information asymmetry, or in the likelihood of dealing with sophisticated informed traders, uninformed traders react by altering bid-ask spreads (Easley and O'Hara, 1987; Glosten and Harris, 1988). Thus, the overall transparency and information environment of stocks tend to be a significant determinant of stock market liquidity (Healy and Palepu, 2001).

Studies suggest that both voluntary and mandatory information disclosures are associated with superior stock market liquidity (Agarwal et al., 2015; Balakrishnan et al., 2014). Extant CSR literature supports the view that CSR disclosures are value-relevant as such disclosures improve transparency while reducing information asymmetry (Cui et al., 2018; Dhaliwal et al., 2011; Orlitzky et al., 2003). This should be applicable for all CSR disclosures irrespective of them being voluntary or mandatory (Dhaliwal et al., 2011). However, particularly under mandatory CSR laws, when it becomes compulsory for firms to disclose all CSR-related information (Ioannou and Serafeim, 2017), this mandatory information disclosure should result in reduced information asymmetry and, consequently, lead to improved stock market liquidity.

Another link between CSR, information asymmetry, and stock market liquidity can be seen through the lens of institutional theory of CSR (Chen and Bouvain, 2009; Martínez-Ferrero and García-Sánchez, 2017). According to this theory, the external institutional forces influence firms' CSR behavior, and such behavior is driven by the process of isomorphism, which includes drivers such as coercion, mimicking, and normative forces (DiMaggio and Powell, 1983). In this context, mandatory CSR regulations fall under the coercive isomorphism strand, wherein firms' CSR behavior is a direct response to the regulation. Leaving corporates on their own to self-regulate may result in significant information asymmetries. Thus, in this context, mandatory CSR regulations should improve the information environment and generate greater confidence within the investor community leading to greater stock market participation and liquidity (Hess, 2007).

The mandatory CSR provisions of S-135 are very specific in terms of what is considered CSR activities and contain several oversight measures, such as a separate CSR committee to oversee CSR spending which brings independence to the management of CSR activities (Dharmapala and Khanna, 2018). Additionally, the provisions require full disclosure of CSR activities via publishing a CSR report detailing the specifics of all CSR expenditures. These provisions of the S-135 law act as external governance mechanisms and should reduce any agency issues relating to mismanagement of CSR funds (Ferrell et al., 2016). Further, the provisions should also result in reduced 'private information seeking and monitoring' costs for the investor, lower the adverse selection problems, and therefore bridge the information asymmetry between the informed and the earlier 'uniformed traders', resulting in higher stock market liquidity (Easley and O'Hara, 1987; Glosten and Milgrom, 1985).

Social and reputational capital - Another body of literature discusses how spending on CSR activities could lead to higher reputational and social capital (Fombrun and Shanley, 1990; Servaes and Tamayo, 2017). First, studies suggest that firms' engagement in CSR helps develop the organization's reputation within the general public and society that they operate in (Fombrun and Shanley, 1990; Turban and Greening, 1997). Studies suggest that reputation plays a key role in stock markets in terms of facilitating trades by alleviating adverse selection and moral hazard problems (Battalio et al., 2007; Klein, 1997). Further, higher reputational capital leads to greater investor confidence and speeds up financial contracts (Boot et al., 1993). Thus, we conjecture that if firms' mandatory spending in various CSR projects helps develop their reputational capital, then such firms should experience superior stock market liquidity through the reputation induced superior investor confidence.

Second, studies suggest that socially responsible firms can create a nexus with the society and environment that they operate in (Dowell et al., 2000; Elfenbein et al., 2012; Konar and Cohen, 2001). Following the arguments of Sacconi and Degli Antoni (2011), Lins et al. (2017) contend that a firm's CSR activities, a measure of its social capital, can lead to better firm performance. Studies suggest that when social capital is low, there is a valuation premium levied by investors on these firms and their participation in the stock market (Guiso et al., 2008, 2004).[6] This conjecture is reinforced by Blau (2017), who shows that trust (a measure of social capital) directly influences the level of stock market liquidity provision. Consistent with these studies, we contend that CSR activities, whether undertaken voluntarily or induced through

[6] From the investors' perspective, Guiso et al. (2008) note "*the decision to invest in stocks requires not only an assessment of the risk-return trade-off given the existing data, but also an act of faith (trust) that the data in our possession are reliable and that the overall system is fair*".

mandatory regulations, should have a similar effect on firms' stock market liquidity. This is because CSR mandates are instrumental in driving the firms to undertake CSR activities which then leads to building social capital eventually bringing with it the benefits discussed hitherto. Specifically, in our empirical context, the provisions of S-135 (such as setting up a CSR committee) ensure that firms direct their CSR expenditures towards social and environmental causes (identified under the law) which should improve their stock market through an increase in their social capital and improved reputation.

In recent years, there is a growing ESG awareness (CSR falls within the purview of ESG) among asset managers and investors leading them into investing in CSR firms (Amel-Zadeh and Serafeim, 2018; Hartzmark and Sussman, 2019; Roy et al., 2020).[7] For instance, more than 700 ESG-focused funds were launched globally by early 2021 attracting around USD 347 billion inflows.[8] The principles of responsible investment (PRI) signatories, developed by an international group of institutional investors, have a common agenda of incorporating ESG issues into their investment decisions, seeking appropriate ESG disclosures, and actively engaging in implementing ESG principles.[9] As a result, analysts are also increasingly seeking additional information from corporations regarding their CSR engagement and providing such information to the investors (Ioannou and Serafeim, 2015). Mandatory CSR regulations make it easier for these stakeholders to identify such CSR firms for investments, thus driving up the market liquidity of these firms.

Finally, mandatory CSR laws reduce the cost of actively seeking and monitoring information regarding CSR activities of firms because both monitoring and enforcement are

[7] There is a growing evidence in literature showing how "socially responsible investment" is gaining tremendous traction among the investment community (see Kumar et al., 2021).
[8] Source Bloomberg, see https://www.bloomberg.com/news/articles/2021-02-10/the-490-billion-boom-in-esg-shows-no-signs-of-slowing-green-insight.
[9] As of 8th November 2021, a total of 4506 financial institutions, asset managers, investment managers and service providers are signatories of PRI. See https://www.unpri.org/signatories/signatory-resources/signatory-directory.

overseen by the regulators. Thus, we conjecture that the reduced information seeking and monitoring costs, decreased information asymmetry, and ease of identification of CSR firms for investments, should all provide a reasonable impetus for more capital flows into corporations mandated by CSR laws. This, in turn, should further drive up the market liquidity of these mandated CSR firms. Thus, given the above discussion that mandatory CSR engagement leads to reduced information asymmetry, higher social and reputational capital, lower agency issues, and increased market participation by investors and analysts, we hypothesize that mandated CSR firms experience higher stock market liquidity, relative to non-CSR firms.

4. Data and variables

We obtain daily stock trading data of firms from the Prowess database maintained by the Centre for Monitoring the Indian Economy (CMIE). Prowess provides data on all firms listed on two major stock exchanges of India: the National Stock Exchange of India Ltd. (NSE) and the Bombay Stock Exchange (BSE). We compute liquidity measures at annual intervals from daily trading data following standard guidelines suggested in the literature (Fong et al., 2017; Goyenko et al., 2009). Next, we combine the yearly liquidity measures with annual firm-level variables, also obtained from the Prowess database for the period of study that covers six years, ranging from 2012 to 2017. Our sample consists of 3,237 unique non-financial firms with 18,177 firm-year observations. We use the Fama-French 17 industry classification for classifying firms into their respective industries based on SIC codes obtained from the S&P Capital IQ (CIQ) database.[10] To mitigate the issues associated with outliers, we winsorize all

[10] S&P Capital IQ provides 4-digit SIC codes for all firms having unique ISIN numbers. We merge the data downloaded from CMIE Prowess with CIQ SIC codes using ISIN numbers.

continuous variables at 2% on both tails. A detailed description of all variables along with their sources is provided in Table A1 of the Appendix.

4.1. Key dependent variable

The key dependent variable of interest in this study is stock market liquidity. Over the years, researchers on market microstructure have developed several measures to proxy for liquidity (or rather illiquidity) that can be broadly classified into two categories namely spread liquidity proxies such as bid-ask spreads and price impact liquidity proxies such as cost-per-dollar-volume (Fong et al., 2017; Goyenko et al., 2009). Since we use daily trading data, we rely on low-frequency proxies to measure stock market liquidity in this study.[11] Drawing on the literature, we incorporate four measures of stock market liquidity as described below:

4.1.1. Amihud illiquidity ratio

Following Amihud (2002), we construct a cost-per-dollar-volume liquidity measure that captures the "daily price response associated with one dollar of trading volume". This illiquidity ratio measure is as shown in the following specification (1):

$$Amihud_{i,t} = Average\left(\frac{|r_{i,d}|}{Volume_{i,d}}\right) \tag{1}$$

where $|r_{i,d}|$ is the absolute value of the return for firm *i*'s stock on day *d*, and $Volume_{i,d}$ is the volume of trade (number of stocks traded times price) for firm *i* on day *d*.[12] We average out the daily ratio throughout year *t* to obtain the annual illiquidity ratio (*Amihud*). A larger (smaller) *Amihud* ratio implies lower (higher) stock market liquidity since illiquid stocks' prices tend to be more sensitive to trades. Prior studies suggest that Amihud's (2002) measure

[11] Fong et al. (2017) suggest that low frequency liquidity proxies require less computational power and time and perform just as well (sometimes even better) as high frequency liquidity measures (based on intraday transaction data).
[12] The ratio is undefined for zero volume days.

is one of the best price impact proxies since it is seen to be highly correlated with other benchmark proxies that measure stock market liquidity (Fong et al., 2017; Goyenko et al., 2009; Marshall et al., 2012).

4.1.2. Zeros

Our second measure is a spread proxy by Lesmond et al. (1999) which is based on a stock's zero return days (no intraday stock return) proportionate to the total trading days. Lesmond et al. (1999) argue that the higher the illiquidity of the stock, the higher will be the zero volume days (days with no stocks traded) and hence zero return days. Further, even on positive volume days, more illiquid stocks could end up having zero returns due to high transaction costs and "less private information acquisition" (Goyenko et al., 2009). The *Zeros* measure is computed as per the following specification (2):

$$Zeros_{i,t} = \frac{(ZRD)_{i,t}}{N_t} \tag{2}$$

where $(ZRD)_{i,t}$ is the total number of zero return days for firm *i*'s stock in year *t* and N_t is the total number of trading days in year *t*. Since the *Zeros* measure is easy to compute and execute, prior studies on stock market liquidity have extensively used this measure, particularly in the emerging market setup where complex stock-related data is scarce (Bekaert et al., 2007; Lesmond, 2005).

4.1.3. High-low spread

We derive a bid-ask spread proxy from daily high-low prices of stocks following Corwin and Schultz (2012) which assumes that a stock's daily high (low) price is generally initiated by buyers (sellers). As a result, the daily high-low prices reflect both stocks' intraday volatilities and their bid-ask spreads. Corwin and Schultz (2012) argue that the volatility is proportionate to the return period whereas the bid-ask spread stays somewhat constant over a short time interval. Thus, two consecutive single days' high-low would reflect the volatility and bid-ask spread for those two single days. Whereas the high-low ranging over a two-day window would reflect two days' volatility and a one-day bid-ask spread. Based on this assumption, We adopt the Corwin and Schultz (2012) measure of spread estimator as per the specification (3):

$$Spread_{i,d} = \frac{2(e^{\alpha_{i,d}} - 1)}{1 + e^{\alpha_{i,d}}} \tag{3}$$

$$\text{where, } \alpha_{i,d} = \frac{\sqrt{2\beta_{i,d}} - \sqrt{\beta_{i,d}}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma_{i,d}}{3 - 2\sqrt{2}}} \tag{4}$$

In specification (4), $\beta_{i,d}$ is computed from the two consecutive single day high-low prices whereas $\gamma_{i,d}$ is calculated from the high-low price within a two-day window. These measures follow specifications (5) and (6), respectively:

$$\beta_{i,d} = \sum_{j=0}^{1} \left[ln \left(\frac{H_{d+j}^{0}}{L_{d+j}^{0}} \right) \right]^2 \tag{5}$$

$$\gamma_{i,d} = \left[ln \left(\frac{H_{d,d+1}^{0}}{L_{d,d+1}^{0}} \right) \right]^2 \tag{6}$$

where $H_{d,d+1}^{0}$ ($L_{d,d+1}^{0}$) is the observed high (low) prices over the two-day window d and $d+1$. For this study, we first measure the $Spread$ on daily intervals for each stock. Next, we average out the $Spread$ over each year to obtain the yearly high-low spread (*HL*) of each firm's stock.[13] For the US stock market, Corwin and Schultz (2012) show that their measure outperforms other spread measures. Similarly, Fong et al. (2017) also show that the high-low spread measure generally performs well in a global context.

[13] We follow all the steps, including making all the adjustments, as suggested in Corwin and Schultz (2012) in our calculations.

4.1.4. FHT measure

Finally, following Fong et al. (2017) we derive a spread proxy by simplifying the LOT measure of Lesmond et al. (1999).[14] The measure is as per the following specification (7):

$$FHT_{i,t} = 2\sigma_{i,t}N^{-1}\left(\frac{1+Z_{i,t}}{2}\right) \tag{7}$$

where $\sigma_{i,t}$ is the standard deviation of daily stock returns computed over the year *t* for stock *i*. $Z_{i,t}$ is the proportion of zero return days for stock *i* in year *t*. $N^{-1}(\ )$ denotes the inverse of the cumulative normal function. *FHT* is simple and easy to compute and it performs relatively well compared to some other spread proxies that require more complex computation (Fong et al., 2017).[15] Hence, several recent studies have incorporated this measure for empirical analysis (Edmans et al., 2013; Marshall et al., 2012).

4.2. Key independent variable

The primary objective of this study is to investigate the causal impact of the CSR mandate (S-135) on firms' stock market liquidity. Following Dharmapala and Khanna (2018), we allocate firms to the treatment group if they satisfy any of the three thresholds specified under the S-135 mandate (i.e., a net worth of INR 5 billion or more, sales of INR 10 billion or more, or a net profit of INR 50 million or more) in any given year from the applicable date of the Companies Act 2013 (i.e., April 1, 2014). Within the PSM-DiD regression framework, our key independent variable of interest is the interaction of the two indicator variables ($Treated_i \times After_t$). The $Treated_i$ dummy takes the value of one for all the treatment group firms and zero for the remaining firms that do not qualify the thresholds of the S-135 (classified

[14] LOT is an effective spread estimator developed by Lesmond et al. (1999) in an effort to directly measure transaction costs based on the assumption that informed (uninformed) trading takes place on non-zero (zero) return days.
[15] Fong et al. (2017) argue that their measure can be computed 1000 times quicker than LOT. The authors also provide the code for computing the *FHT* measure in their paper.

as control group firms).[16] The second indicator variable, $After_t$ takes the value of one for the three years following the enforcement of S-135 (i.e., FY 2015-2017; post-S-135) and takes the value of zero for the three years prior to the enactment of S-135 (i.e., FY 2012-2014; pre-S-135).

4.3. Covariates

Drawing on the prior literature, in this study we use several covariates that are highly associated with firms' stock market liquidity. The covariates serve two purposes. First, following the approach of Rosenbaum and Rubin (1983, 1985), within the empirical context, we use several key firm-level variables for Propensity Score Matching (PSM) to generate highly comparable treated and control group firms before the implementation of S-135. Such pre-evaluation is crucial for reliably establishing causality as it controls for heterogeneous expectations in the post-CSR mandate period between treated and control groups (Rubin, 1997). Moreover, an efficient PSM creates near randomization that could control for all potential time-variant and invariant factors that may affect stock market liquidity within the PSM-DiD framework as such factors should have "homogenous effects" on both the treated and control group firms in the post-CSR mandate period (Rubin and Waterman, 2006).

Second, we include all the covariates in the multivariate regression models, to generate more accurate regression estimates since the incorporation of covariates in regression models is more likely to produce a lower residual variance.[17] The covariates for this study are briefly discussed below.

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[16] One issue that could affect this identification strategy is self-selection bias, where firms endogenously choose to get affected or unaffected by S-135 by manipulating their threshold figures. However, Manchiraju and Rajgopal (2017) find no such tampering with the accounting data by Indian firms prior to the enactment of S-135.
[17] Angrist and Pischke (2008) note, *"A regression along this point is the result that even in a scenario with no omitted variable bias, the long regression generates more precise estimates of the coefficients on the variables*

Prior studies suggest that large firms provide better information and greater visibility to investors and, as a result, stocks of large firms exhibit superior liquidity due to higher investor interest, higher trading frequency, and lower adverse selection (Gompers and Metrick, 2001; Harris, 1994). Thus, we take firm size (*Size*), calculated as the natural logarithm of total assets, as a key firm-level covariate (Pham, 2020; Thapa et al., 2020). Further, the literature suggests that firms' capital structure choices could influence stock market liquidity as firms with higher levels of information asymmetry rely more on debt capital (Andres et al., 2014; Myers and Majluf, 1984). As a result, we include leverage (*Leverage*), computed as the debt to equity ratio, as a key covariate (Koirala et al., 2020). Firms holding more liquid assets experience higher stock market liquidity as retention (investment) of liquid assets results in more certainty (uncertainty) of future cash flows (Gopalan et al., 2012; Huang and Mazouz, 2018). Hence, we also incorporate firms' cash holding (*Cash*), calculated as the "sum of year-end cash and short-term securities" scaled by total sales as a covariate (Roy et al., 2020).

Studies suggest that a firm's level of tangible investments, or tangibility, is positively associated with stock market liquidity since payoffs from tangible assets are more observable to investors, resulting in lower information asymmetry (Chung et al., 2010; Pham, 2020). We take the firm's capital expenditure scaled by total assets (*CapEx*) as a covariate for tangibility (Gopalan et al., 2012).[18] Institutional investors improve firm-level transparency and the information environment by directly influencing corporate governance mechanisms (Boone and White, 2015; McCahery et al., 2016). Thus, a higher level of institutional ownership should be associated with higher stock market liquidity. We control for the total percentage of share

included in short regression whenever these variables have some predictive power for outcomes because these covariates lead to a smaller residual variance" (p.62).

[18] Capital expenditure is calculated as the annual additions to property, plant, and equipment (tangible assets) following Rao et al. (2021).

ownership by institutional investors (*IO*) as our final firm-level covariate (Gompers and Metrick, 2001).

We also incorporate some key stock market characteristics that are highly correlated with stock market liquidity in our regressions to further increase the accuracy of the estimates. Studies suggest that analysts provide greater informational efficiency in the market and that firms with higher analyst following tend to have higher stock market liquidity due to higher trading activity (Charitou et al., 2019; Roulstone, 2003). Additionally, stock return volatility seems to have a significantly positive correlation with stock market liquidity (Bali et al., 2005). Furthermore, share turnover reflects investors' interest in firms' stocks and is positively related to stock market liquidity (Gao et al., 2014). Hence, we include the number of analysts following the stock (*Analyst*), the annual average daily stock return volatility (*Volatility*), and the daily average share turnover (*Turnover)*, calculated as the daily total number of shares traded as a percentage of daily shares outstanding in our regression models. We lag all covariates in our regression models by one year to avoid potential concerns about reverse causality.

4.4. Descriptive statistics

We present the descriptive statistics of the key variables in Table 1 for the entire sample as well as for the pre-S-135 (i.e., FY 2012-2014) and post-S-135 (i.e., FY 2015-2017) periods. Panel A of Table 1 reports the summary statistics (mean values with standard deviations) of all liquidity measures. The overall sample mean values are 8.361 for *Amihud*, 0.277 for *Zeros*, 0.125 for *HL*, and 0.328 for *FHT*. It is seen that *Amihud* significantly (at the 1% level) decreases in the post-S-135 period, compared to the pre-S-135 period by 3.77 (or by 36.70%). Similarly, relative to their pre-S-135 period mean values, both *HL* and *FHT* seem to sharply decline in the post-CSR period by 6.20% and 5.62%, respectively. Finally, the mean difference for *Zeros* between pre- and post-S-135 periods is observed to be negative (-0.007) and significant at the

10% level. These results are indicative that the overall stock market liquidity increased in the post-CSR mandate period and provide a suggestion that the improved stock market liquidity could be driven, at least partially, by the CSR mandate.

Panel B of Table 1 shows the summary statistics for all of the key firm-level covariates (*Size*, *Leverage*, *Cash*, *CapEx*, and *IO*) and stock market characteristics (*Analyst*, *Volatility*, and *Turnover*). It is evident that *Leverage* sharply decreases in the post-S-135 period by 8.25% (0.087/1.055). Such a decline in *Leverage* could be driven by the CSR induced lower cost of equity whereby CSR firms may have achieved easier access to equity capital and relied less on debt capital (El Ghoul et al., 2011). Further, *CapEx* seems to decline in the post-CSR mandate period as well, which could be an indication that CSR firms, having better investment efficiency, may require less tangible investments (Benlemlih and Bitar, 2018). As with stock market characteristics, it can be observed that both *Volatility* and *Turnover* significantly (at the 1% level) increase in the post-S-135 period, which might have resulted from the increased trading of CSR stocks having lower information asymmetries (Cui et al., 2018; Dhaliwal et al., 2011). The rest of the variables do not seem to change significantly in the post-S-135 period.

[Table 1 about here]

5. Empirical strategy: Propensity score matching (PSM)

As noted earlier, we exploit S-135 as an exogenous shock to firms' CSR activities and use difference-in-differences (DiD) as our main identification strategy in this study. However, a key prerequisite for effectively implementing a shock-based quasi-experiment is to have highly comparable groups of treated and control firms that should have equal expectations in treatment outcomes in the post-shock period (Atanasov and Black, 2021, 2016). Hence, we first check the comparability of treated and control groups by running t-tests of mean differences in key firm-level covariates (*Size*, *Leverage*, *Cash*, *CapEx*, and *IO*) between all treated and control firms before the enforcement of S-135 (i.e., FY 2012-2014).

The results, presented in Panel A of Table 2, show that treated and control groups are significantly different (at 1% significance levels) in terms of their covariates and, thus, are not comparable. To resolve this potential issue, we apply the propensity score matching (PSM) near randomization technique to obtain highly comparable treated and control firm pairs (Koirala et al., 2020; Thapa et al., 2020). To do so, we first run a probit regression for the pre-S-135 period on the full sample of treated and control group firms as identified by S-135 for generating propensity scores as per specification (8):

$$Treated_i = \alpha + \boldsymbol{X_{it}}.\boldsymbol{\beta}' + \vartheta_j + \varepsilon_{it} \tag{8}$$

Where the dependent variable is the $Treated_i$, as defined in Section 4.2. $\boldsymbol{X_{it}}$ is the vector of key firm-level covariates namely *Size*, *Leverage*, *Cash*, *CapEx*, and *IO*, all as defined in Section 4.2. We also include ϑ_j, which is the industry fixed effects. Next, using the propensity scores generated from specification (8), we employ the nearest neighbor caliper algorithm with replacement to match a set of treated and control firms before the enforcement of S-135 (Rosenbaum and Rubin, 1985; Smith and Todd, 2005).[19] The PSM algorithm generates 514 distinct pairs of matched treated and control firms. To test whether the PSM technique reduced variations in covariates between control and treated groups before S-135, we re-run specification (8) on the matched pair of firms. The estimates obtained from specification (8) for both the pre- and post-matched samples are presented in Panel B of Table 2.

[19] Our sample originally contains 1,590 control and 1,647 treated firms (Almost evenly distributed). Thus, instead of exact matching, we apply nearest neighbor matching with a highly restrictive caliper radius of 0.01%. We acknowledge that such a restrictive procedure considerably reduces the number of treated and control firms in our matched sub-sample. However, such restricted near-randomization approach results in almost identical treated and control groups, which are immune to any heterogenous characteristics bias. Moreover, matching with replacement reduces the propensity score distance amongst the matched treated and control group firms which, in turn, reduces PSM bias (Dehejia and Wahba, 2002).

As illustrated in Model [2] of Panel B in Table 2, none of the covariates seem to be significant, clearly indicating very little dissimilarity among the matched treated and control group firms. Additionally, the pseudo-R^2 declines substantially from 0.28 obtained in the pre-match probit (Model [1]) to only 0.02 in the post-match diagnostic regression (Model [2]), suggesting that the explanatory power of the probit model is significantly diminished for the matched pair of treated and control subsample of firms.

[Table 2 about here]

To confirm pre-treatment balance among covariates as suggested by Atanasov and Black (2021) for our shock-based PSM-DiD approach, we plot the standardized difference and standardized percentage bias graphs between unmatched and matched sample covariates in Figure 1a and 1b, respectively. The standardized difference contrasts the variation within covariate means between treated and control groups in units of the pooled standard deviation and, unlike other statistical methods, is not affected by sample size (Austin, 2009). The closer the standardized difference is to zero, the higher the covariate balance between treated and control groups. Figure 1a shows the standardized difference in all the covariates are close to zero for the PSM matched sample (circle-shaped figures) compared to the larger values as observed in the covariates for the unmatched sample (diamond-shaped figures).

The standardized percentage bias examines the interval in marginal covariate distribution and shows the reduction in bias among covariates before and after matching (Rosenbaum and Rubin, 1985). Figure 1b reveals that the biases among covariates for the matched sample (circle-shaped figures) are within the acceptable range of ±5%, whereas we observe a large covariate bias for the unmatched sample (diamond-shaped figures). Overall, all the PSM diagnostic tests confirm that the PSM technique significantly reduced the probable observational dissimilarities among matched treated and control groups before the enforcement of the CSR mandate.

[Figure 1 about here]

6. Empirical results

6.1. Univariate difference-in-differences estimates

We begin our empirical investigation by plotting the parallel trend of the liquidity measure (*Amihud*) of the PSM-matched treated and control group firms. Figure 2a shows that before the enactment of the S-135 both treated and control have a clear parallel trend, whereas the treated group's illiquidity falls more than the control group in post-S-135 years. Additionally, in Figure 2b we present the trend of the DiD coefficient. We can see that the DiD coefficient estimate moves around zero and is insignificant as shown by the wide confidence interval (CI) and in the pre-S-135 period, whereas in the post-S-135 the DiD coefficient is significantly lower than zero with a very narrow CI.

[Figure 2 about here]

Next, we run the univariate difference-in-differences (DiD) analysis for all four stock market liquidity measures (*Amihud*, *Zeros*, *HL*, and *FHT*) using the propensity score matched control and treated group firms for the study period 2012-2017.

[Table 3 about here]

From the results presented in Table 3, it can be observed that the univariate DiD estimates for all the stock market liquidity proxies are negative and highly significant, at least at the 5% significance level. For instance, the DiD estimate is -2.115 for *Amihud* which implies that relative to the pre-S-135 period, treated firms' stocks experienced a lower Amihud illiquidity ratio by 2.115 on average, compared to control firms' stocks in the post-S-135 period. Comparing this negative differential value with the pre-S-135 mean value of *Amihud* (10.288), the decrease seems to be substantial and economically meaningful as it indicates a 20.56% decline in price impact for treated firms' stocks, relative to control firms' stocks in the post-S-135 period. Applying similar calculations, we see that treated firms' stocks experienced a 13.88% decrease in terms of *Zeros*, a 32.56% decrease in terms of *HL*, and a 23.96% decrease in terms of *FHT*, compared to control firms' stocks in the post-S-135 period. Overall, these initial results support our hypothesis that mandated CSR firms experience higher stock market liquidity (i.e., significantly low illiquidity), relative to non-CSR firms.

6.2. Multivariate propensity score matched difference-in-differences estimates

Although the univariate DiD analysis indicates that mandatory CSR engagement induces superior stock market liquidity for mandated CSR firms, for more rigor in establishing causality, we extend our empirical investigation by employing a multivariate regression-based PSM-DiD. As such, we run the following regression-based DiD as per specification (9) on the propensity score matched treated and control firms:

$$SML_{it} = \alpha + \beta(Treated_i \times After_t) + \boldsymbol{X}_{it-1}\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it} \qquad (9)$$

where the dependent variable SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Section 4.1, of firm *i* in year *t*. $Treated_i$ and $After_t$ are indicator variables, as defined in Section 4.2. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO*, and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Section 4.3. γ_i and τ_t control for firm and year fixed effects, respectively within the panel regressions. Finally, ε_{it} is the error term. Standard errors are clustered at the firm level in all regressions. The key coefficient of interest is from the interaction term ($Treated_i \times After_t$) or β, which is the DiD estimator that shows the causal impact of the CSR mandate on complying firms' stock market liquidity. We report the multivariate DiD regression results in Table 4.

[Table 4 about here]

Table 4 shows the DiD coefficients to be negative and highly significant (at least at the 5% level) for all the stock market liquidity measures. For instance, *Amihud* has a negative DiD coefficient of -2.252, which implies that treated firms' Amihud's illiquidity ratio was lower by 2.252 in the post-S-135 period compared to control firms' stocks. When we compare this decline with the pre-S-135 mean value of *Amihud* for all firms' stocks (10.288), it is evident that treated firms' stocks had about 21.89% lower price impact, compared to control firms' stocks. Employing similar calculations for the spread proxies (*Zeros*, *HL*, and *FHT*), we find that treated firms' stocks also had lower spreads in the range of 9.61% (*Zeros*) to 30.23% (*HL*) on average in the post-CSR mandate period, relative to control firms' stocks.[20] [21] Overall, the results are in line with the univariate DiD estimates in Table 3 in terms of both significance and economic magnitude, providing further support to our hypothesis.

6.3. Robustness tests

In this section, we undertake four robustness checks of our main findings from the PSM-DiD analysis. These tests include analysis with alternative treated and control group firms, analysis with alternative stock market liquidity measures, a placebo test that incorporates an alternative period, and a multivariate regression discontinuity design (MRDD) analysis.

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[20] As an additional robustness check, we also control for reputation and visibility by taking firms' goodwill scaled by total assets (*Goodwill*), and the natural logarithm of age (*Age*) in our multivariate PSM-DiD regressions (Lin et al., 2015). The results, presented in Table A2 of the Appendix, are in line with our main findings.

[21] Extraordinary revenues, PAT, restructuring or mergers & acquisition events can impact the S-135 thresholds, and thus have a direct influence on the treated firms. We, therefore, drop treated firms that were subjected to any extraordinary events in the post-S-135 period along with their corresponding control group firm pairs and re-run the empirical specification (9). The results, presented in Table A3 of the Appendix, from this additional robustness test remain qualitatively similar to our main empirical results.

6.3.1. Alternative treated and control group firms

There is some evidence that a handful of firms (the treated group as defined in Section 4.2) were already voluntarily spending on CSR activities before the enforcement of S-135. We, therefore, run a robustness test for our main empirical specification (9) by using an alternative definition for the treated and control groups. Accordingly, in specification (9) firms that did not spend on CSR before the mandatory CSR rule but incurred CSR expenditure after the introduction of S-135 are classified as treatment firms ($Treated_i = 1$), and firms that did not spend on CSR before and after the introduction of S-135 as control firms ($Treated_i = 0$). The results, presented in Table 5, show the DiD coefficients to be significantly negative at least at the 5% level of significance. Similar to the main results all four liquidity measures *Amihud*, *Zeros*, *HL*, and *FHT* of the treated firms declined significantly in the post-CSR mandate period, relative to control firms' stocks. DiD coefficient of -1.325 for *Amihud*, implies that treated firms' Amihud's illiquidity ratio was lower by 1.325 on average in the post-S-135 period compared to control firms' stocks. When we compare this decline with the pre-S-135 mean value of *Amihud* for all firms' stocks (10.288), we find that treated firms' stocks had about 12.88% lower price impact, compared to control firms' stocks. Employing similar calculations for the spread proxies, we find that treated firms' stocks also had lower spreads of 11.03% (Zeros), 6.20% (HL), and 16.57% (FHT) on average in the post-CSR mandate period, relative to control firms' stocks. [22] Overall, the results are in line with our main findings in Subsections 6.1 and 6.2.

[Table 5 about here]

[22] We run the PSM-DiD regression using the alternative treated and control group firms and find similar results. The results are presented in Table A4 of the Appendix.

6.3.2. Alternative stock market liquidity measures

As a further robustness analysis, we use additional stock market liquidity measures in our analysis. Drawing on the literature, we choose four additional stock market liquidity measures, namely the Amivest liquidity ratio (*Amivest*) of Amihud et al. (1997), the *Zeros2* measure of Goyenko et al. (2009), the serial covariance of price change spread measure (*Roll*) of Roll (1984), and the gamma price impact measure (*Gamma*) of Pástor and Stambaugh (2003). We employ these alternative measures as the dependent variables in the specification (9) and derive the regression estimates from our PSM matched treated and control groups. We tabulate the results for the alternative stock market liquidity measures in Table 6.

The DiD coefficients in Table 6 seem to be significant in general (at least at the 5% level) and carry the expected signs in line with our main results in Table 4. For instance, the DiD coefficient for *Amivest* is positive, suggesting that relative to the pre-S-135 period, in the post-S-135 period treated firms' stocks had higher Amivest liquidity ratios, compared to control firms' stocks. Furthermore, and as expected, the DiD coefficients for the two alternative spread estimators (*Zeros2* and *Roll*) are negative. Finally, similar to our main results for *Amihud* in Table 4, the DiD coefficient for the gamma price impact measure (*Gamma*) is also negative. Overall, these results suggest that the mandated CSR firms obtained higher stock market liquidity, relative to non-CSR firms in the post-CSR mandate period and, thus, provide additional support to our hypothesis.

[Table 6 about here]

6.3.3. Placebo test

Our main findings are based on the implementation of S-135 in FY 2015 that directly caused exogenous variation in the key independent variable, CSR activity. However, it is possible that the findings are due to a pre-existing trend or merely reflect the effect of a shock that occurred before the enforcement of S-135. To rule out this possibility, we design a placebo test where we take 2010 as a false exogenous shock year and derive regression estimates as per specification (9).

We run the placebo test on all four of our primary stock market liquidity measures (*Amihud*, *Zeros*, *HL*, and *FHT*) using the same PSM matched treated and control groups as in our baseline analysis. The mandatory CSR related information first came to light in the year 2010 and hence the choice of 2010 as the false shock year. Any pre-existing trends would reflect in the placebo DiD analysis. Similar to our baseline analysis, we take three years (2007-2009) before 2010 as the false pre-S-135 period (i.e., $After_t$=0) and the following three years (2010-2012) as the false post-CSR mandate period (i.e., $After_t$=1). We report the placebo regression results in Table 7. We find that the placebo DiD coefficients are insignificant across all four liquidity measures. Thus, the placebo test results eliminate any possibility that our main baseline results are due to any previously pre-existing trends.

[Table 7 about here]

6.3.4. Multivariate regression discontinuity design (MRDD)

We extend our analysis by running a Regression Discontinuity (RD) test around the cut-off points of the size thresholds of S-135 to determine the localized treatment effect of the CSR mandate on firms' stock market liquidity. However, since S-135 has three thresholds of assignment for determining treatment status, we rely on the binding-score Multivariate Regression Discontinuity Design (MRDD) test following Manchiraju and Rajgopal (2017) and Reardon and Robinson (2012). The binding-score approach of MRDD allows multiple assignment variables to be combined into a single rating variable (*BScore*) and estimate the overall treatment effect within a given bandwidth.

To generate the single rating variable (*BScore*), we first center each of the three assignment variables of S-135 on their respective cut-offs (zero) by using their respective threshold levels (INR 5 billion for net worth, INR 10 billion for sales, and INR 50 million for net profit). Next, we generate the single new rating variable (*BScore*) by taking the minimum of the three rating variables that are centered on zero (see Manchiraju and Rajgopal, 2017; and Reardon and Robinson, 2012 for details).[23]

For our MRDD analysis, following Manchiraju and Rajgopal (2017), we set the maximum bandwidth of the running variable (*BScore*) to 50% (i.e., ±0.5).[24] We present the MRDD plots for all four liquidity measures (*Amihud*, *Zeros*, *HL*, and *FHT*) for the years 2015-2016 in Figure 3. Clear discontinuity is observed around the cut-off (zero) for all four liquidity measures and treated firms seem to have lower illiquidity, relative to control firms in two years post-S-135 period. Overall, the graphical analysis indicates an average positive treatment effect of S-135 on stock market liquidity for treated firms.

[Figure 3 about here]

Next, we run the following regression-based MRDD analysis on the cross-section of firms for the two years post-S-135 (i.e., FY ending 2015 and 2016) as per specification (10):

$$SML_{it} = \alpha + \lambda . S135_i + \boldsymbol{X_{it-1}} . \boldsymbol{\delta}' + \vartheta_j + \varepsilon_{it} \quad (10)$$

where the dependent variable SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Section 4.1, of firm *i* in year *t*. $S135_i$ is a dummy variable that is set to one if firm *i*'s running variable, *BScore* ≥ 0 and zero if *BScore* < 0. $\boldsymbol{X_{it-1}}$ is a vector of

[23] We follow the following steps. If the three assignment variables are net worth (NW_i), sales (NS_i), and net profit (NP_i) and if S-135 have a threshold cut-off of NWc, NSc and NPc respectively, then for each firm (*i*), the values centered on zero for each assignment variable are calculated as $NW_i^z=(NW_i-NWc)/NWc$; $NS_i^z=(NS_i-NSc)/NSc$ and $NP_i^z=(NP_i-NPc)/NPc$. The single rating variable ($BScore_i$) is then generated as: $BScore_i$ = minimum (NW_i^z, NS_i^z, NP_i^z)

[24] Our results do not change qualitatively when we apply different bandwidths of the $BScore_i$ (i.e., 25%, 75%, and 100%). Thus, our findings from the MRDD analysis are not driven by a particular choice of bandwidth.

one-year lagged covariates, as per specification (9). ϑ_j controls for industry fixed effects using the Fama-French 17 industry classification. The average treatment effect of S-135 on stock market liquidity is captured by the coefficient of the indicator variable $S135_i$ or λ. The results from the regression-based MRDD are presented in Table 8.

Similar to our PSM-DiD approach, the MRDD estimates indicate an overall negative treatment effect (significant at least at the 5% level of significance) of S-135 on all four stock market liquidity measures. The results show that, in the two years post-S-135, treated firms' stocks had lower price impact (-2.074 in terms of *Amihud*) and lower spreads (-0.035 in terms of *Zeros*, -0.048 in terms of *HL*, and -0.154 in terms of *FHT*), compared to control firms' stocks. In economic terms, these figures translate into a decrease in price impact by 20.16% and a decrease in transaction costs by 12.46% (*Zeros*) to 45.56% (*FHT*) for treated firms, relative to control firms in the two years post-S-135.[25] Overall, the MRDD estimates are in line with our PSM-DiD results and provide further support to our hypothesis.

[Table 8 about here]

6.3.5. Cross-sectional heterogeneity

We conduct additional cross-sectional analyses on whether different heterogeneous characteristics of firms such as group affiliation, percentage of the promotor and institutional ownership, import revenues, and geographic presence matter when it comes to CSR expenditure and stock market liquidity. Similar to Rao et al. (2021), we conduct several subsample analyses to capture the effect of the cross-sectional heterogeneity of the firms

[25] Using pre-S-135 mean values of stock liquidity measures.

discussed above on firms' stock liquidity and run the empirical specification (9) for each subsample and present the results in Table 9.[26]

Business group firms have significant operational and financial interlinkages (Gopalan et al., 2007; Thapa et al., 2020), and having group affiliation means an efficient allocation of resources within the group (Chang and Hong, 2000). Further activities of the group-affiliated firms can have an overall spillover effect on the group's reputation (Buchuk et al., 2014; Gopalan et al., 2007). However, unaffiliated, non-group firms do not have these advantages, and any opportunity to increase their social and reputational capital should augur well for the non-group firms. Specification (9) results for group affiliated firms and non-group affiliated firms are presented in the Table 9, Model [1] and Model [2] respectively. While both DiD coefficients are negative, the non-group affiliated firms' sub-sample has a significantly negative DiD coefficient of -2.845, in line with our conjecture that CSR mandates should have a more positive impact on non-group firms' social and reputational capital and, consequently, on their stock market liquidity. These results are similar to the arguments put forward by Thapa et al. (2020) with regards to why non-group firms may have more significant impact in comparison to the group affiliates using a regulatory shock in a different empirical context.

Studies suggest that firms with high promoter (concentrated) ownership in emerging markets suffer from agency issues and poor corporate governance due to managerial and family control (Leuz et al., 2009; Villalonga and Amit, 2006). Moreover, the agency issues in these firms seem to be primarily agency type-2 that is the differences between majority and minority shareholders (Bhaumik and Selarka, 2012). As a result, such firms are associated with increased informational opacity and heightened information asymmetry, which should lead to

[26] For brevity, we only show the results with *Amihud* as our main dependent variable (proxy for stock market liquidity) for our cross-sectional heterogeneity analysis. We get similar results when we employ other stock market liquidity measures as the dependent variable for this analysis.

lower stock liquidity (Anderson et al., 2009). Owing to the influencing effects ownership concentration may have on the firm, we rerun the main empirical specification on the high (above median) and low promoter (below median) ownership subsamples. Accordingly, we find that firms with high promoter ownership have a significant DiD coefficient of -2.309 (Model [3]) in comparison to low promotor ownership (Model [4]). These results indicate that the CSR mandate helps reduce the greater information asymmetry associated with highly concentrated ownership and improve stock liquidity in emerging markets.

Next, we conduct the subsample analysis of specification (9) on high and low institutional ownership firms. The literature suggests that institutional investors play a significant role in improving the corporate governance of firms through their "voice" or "exit" strategy (McCahery et al., 2016). Moreover, firms with higher institutional ownership seem to maintain superior transparency and a better information environment (Boone and White, 2015). Hence, we conjecture that firms with low institutional ownership should suffer from lower stock liquidity due to poor corporate governance and higher informational opacity. Thus, relative to high institutional ownership firms, such low institutional ownership firms should benefit more from the mandatory CSR-induced reduction in information asymmetry and agency issues. This, therefore, should lead to higher stock market liquidity among these firms. The DiD coefficients of Model [5] and Model [6] seem to support this conjecture as firms with lower institutional ownership seem to obtain significantly higher stock market liquidity in the post-S-135 period whereas the effect seems to be non-significant for high institutional ownership firms.

Foreign revenues can have a direct impact on the revenue thresholds of the S-135. This entails that firms with foreign revenues have an international presence, and any CSR activity can directly impact its international reputation and standing. Moreover, mandatory CSR activities could lead to better product-market differentiation (Albuquerque et al., 2019). Thus, we conjecture that firms that undertake CSR activities should stand to gain more social/reputational capital internationally, which will attract more international investments and, in turn, drive up the stock market liquidity (Roy et al., 2020). The results seem to be in line with this conjecture. We observe that while CSR mandate benefits in terms of increased liquidity for both firms with (Model [7]) and without foreign sales (Model [8]), the DiD coefficient for firms with foreign sales is significant at a 5 percent significance level.

Finally, we classify firms into those that have operations in either a single or multiple geographic locations using the data available from S&P Capital IQ. In line with the social/reputational capital theory as discussed in Section (3), we conjecture that firms with multiple geographic locations should benefit more from mandatory CSR activities when compared to single location firms. Results presented in Model [9] for single location and Model [10] for multiple location firms subsample seem to be in line with this argument. CSR firms with multiple locations may enjoy a higher social and reputational capital due to the multiplier effect from their multi-location presence. Further investigations in future research are needed to shed additional light on this multi-location conjecture.

[Table 9 about here]

6.4. Actual CSR expenditure and stock market liquidity

Since CSR expenditure under S-135 is a "comply or explain" basis, some of the treated firms in both of our PSM-DiD and MRDD analyses may not spend on CSR, but rather explain non-compliance. As a result, our quasi-natural experiment set-up may not completely capture the effect of CSR performance on stock market liquidity.[27] To alleviate this issue, we investigate how firm-level actual CSR expenditure is associated with stock market liquidity, by taking

[27] However, except expenditure, all other CSR related disclosures are mandatory under S-135. Hence, even though the effect of CSR performance might be partially captured, the effect of CSR on stock market liquidity through the disclosure channel is fully identified in both of our PSM-DiD and MRDD analysis.

actual CSR expenditure values as a direct indicator of CSR performance. We also conjecture that such analysis should allow us to identify the social and reputational channels through which CSR affects stock market liquidity as firms spending on CSR activities should obtain higher social and reputational capital (Fombrun and Shanley, 1990; Servaes and Tamayo, 2017).

Following the CSR reform in India, complying firms are required to disclose project-level information about their CSR activity each year under various development sectors that are allowed under S-135. We hand collect the CSR expenditure details of all complying firms for the years 2015 to 2017 from the Indian Ministry of Corporate affairs CSR portal.[28] Next, we broadly re-classify the actual CSR expenditures into four categories namely education and training (*EDU*), healthcare (*HLTH*), social justice and welfare (*SOC*), and environment (*ENV*) based on the development sectors.[29] Such classification further enables us to investigate how and, to what degree, heterogenous CSR activities are associated with stock market liquidity. We run the following baseline regression as per specification (11) on our PSM matched subsample for testing the relationship between actual CSR expenditure and stock market liquidity:

$$SML_{it} = \alpha + \omega.\boldsymbol{CSR_{it}} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta}' + \vartheta_j + \tau_t + \varepsilon_{it} \tag{11}$$

where the dependent variable SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Section 4.1, of firm *i* in year *t*. Depending on the model, $\boldsymbol{CSR_{it}}$ is either the natural logarithm of total CSR expenditure or a vector of heterogenous CSR expenditures (*EDU*, *HLTH*, *SOC*, and *ENV*) scaled by total CSR expenditure for firm *i* in year

[28] Prior to the enforcement of S-135 (i.e., before FY 2015), such CSR project level data is not available. Hence, we conduct our analysis only for the post-S-135 period. We take the CSR expenditure as zero if a firm does not have any CSR expenditure data.

[29] We do not consider projects for which development sectors are not disclosed. The details of the total CSR expenditure under various development sectors and their reclassification are provided in Table A5 of Appendix.

t. $\boldsymbol{X_{it-1}}$ is a vector of one-year lagged covariates, as per specification (9). ϑ_j and τ_t control for industry and year fixed effects, respectively.

We present the regression estimates from specification (11) in Table 10. The key independent variable ($\boldsymbol{CSR_{it}}$) is the natural logarithm of total CSR expenditure in Models [1] to [4], whereas in Models [5] to [8] it is the vector of different types of scaled CSR expenditures, as described before. It is observed that across all four liquidity measures in Models [1] to [4], the aggregate CSR expenditure coefficients are negative and highly significant at the 1% level of significance. The results indicate that firms that spent on CSR activities, due to S-135 compliance, experienced superior stock market liquidity, relative to non-CSR firms in the post-S-135 period. These results are in line with our main results in Section 6.3 and provide support to our conjecture that CSR improves stock market liquidity through the social and reputation capital when firms spend on CSR activities.[30]

[Table 10 about here]

From the results for heterogenous CSR expenditures in Models [5] to [8], it is apparent that not all types of CSR expenditures are strongly associated with stock market liquidity. We observe that CSR expenditures allocated primarily in education (*EDU*) and healthcare (*HLTH*) projects are significantly associated with higher stock market liquidity, whereas the association is generally insignificant for social justice and welfare (*SOC*) and environment (*ENV*) projects. We conjecture that in an emerging market, where poverty is a major concern, firms spending on projects associated with satisfying the most basic human needs such as education and

[30] To remove any doubt of self-selection bias and to improve confidence in our results from specification (11), we conduct an exogenous shock-based instrumental variable (IV) analysis on our PSM matched sample following the literature (Atanasov and Black, 2021; Iliev, 2010). We explain the approach and the results from this analysis in detail in the Internet Appendix. Overall, our PSM shock IV estimates mitigate any issue of self-selection bias of our results from specification (11) and provide further robustness check.

healthcare might be able to create greater social impact, resulting in higher social capital. Further, when compared to social justice and environment expenditures, investments in education and healthcare could plausibly gain more attention with the local populace helping the firms to obtain more reputation. Hence, firms focusing on education and healthcare projects as part of their mandatory CSR engagement could obtain superior stock market liquidity through increased social and reputational capital.

6.5. Value implication of CSR induced stock market liquidity

So far, our empirical investigation has revealed a significant positive relationship between mandated CSR expenditure and firms' stock market liquidity. In this subsection, we investigate the value implication of such CSR induced higher stock market liquidity. Extant literature suggests that superior stock market liquidity is associated with lower cost of capital (Amihud and Mendelson, 1986; Diamond and Verrecchia, 1991). As a result, better stock market liquidity results in higher market value (Fang et al., 2009).

Further, firms with superior stock liquidity seem to attract higher institutional and foreign ownership (Ferreira and Matos, 2008; Gompers and Metrick, 2001). Thus, firms with more liquid stocks tend to obtain higher stock prices driven by increased investor demand (Gompers and Metrick, 2001; Holmström and Tirole, 1993). In line with these studies, we conjecture that the mandated CSR expenditure induced higher stock market liquidity should improve the market value of CSR firms in the long run.

To investigate the value implication of mandated CSR induced higher stock market liquidity, we conduct a series of mediation analyses following the literature (Francis et al., 2021; Lang et al., 2012). According to this method, we first need to establish that there is a significant positive effect of mandatory CSR (in our case the interaction term $Treated_i$ ×

$After_t$ or DiD) on firm value. To establish this link, we run the following baseline regression on our PSM matched sample:

$$Value_{it+1} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it} \quad (12)$$

where the dependent variable $Value_{it+1}$ is the market value, proxied by either Tobin's Q (*Tobin's Q*) or the market-to-book ratio (*MB*), of firm *i* in the lead year *t+1*. $Treated_i$ and $After_t$ are indicator variables as in specification (9). $\boldsymbol{X}_{it}$ is a vector of covariates including *Size*, *Leverage*, *Cash*, *CapEx*, *IO*, *Analyst*, *Volatility*, and *Turnover*, all as defined in Section 4.3. γ_i and τ_t are firm and year fixed effects, respectively. The key coefficient of interest is from the interaction DiD term ($Treated_i \times After_t$). We present the results in Model [1] (*Tobin's Q*) and Model [6] (*MB*) of Table 11. The positive and highly significant (at the 1% level) DiD coefficients for both the market value proxies (*Tobin's Q* and *MB*) indicate that, in the post-CSR mandate period, treated firms obtained higher market-based valuations (18.4% in terms of *Tobin's Q* and 35.8% in terms of *MB*) on average, relative to control firms.

To show the mediation effect of stock market liquidity on the mandatory CSR induced higher firm value, we next regress firm value (*Tobin's Q* or *MB*) on both the DiD and the stock market liquidity measures (*Amihud*, *Zeros*, *HL*, or *FHT*) with all other covariates alongside firm and year fixed effects. If stock market liquidity mediates the association between mandatory CSR and firm value, then the coefficients on the stock market liquidity measures should be significant and the magnitude/significance of the DiD coefficients should be reduced after the stock market liquidity measures are added to the regression. We present the mediation results in Models [2] to [5] (*Tobin's Q*) and Models [7] to [10] (*MB*). We find the coefficients on the stock market liquidity measures to be generally significant (at least at the 5% level). Further, the results indicate that there is a general reduction in the DiD coefficients (about 2.17% to 3.80% in terms of *Tobin's Q* and 2.79% to 5.87% in terms of *MB*), which represents the mediation effect of stock market liquidity on the mandatory CSR (DiD) induced higher firm value. To test the significance of the mediation effect, we run Sobel (1982) tests and find the mediation effect to be generally significant (p-value at least <0.05). Overall, our mediation analysis provides evidence that mandatory CSR activities improve the market value of firms in the long run via the route of increased stock market liquidity.

[Table 11 about here]

7. Conclusion

Studies document firms' stock market liquidity as one of the most crucial financial parameters that are directly linked with firms' financial performance and growth (Guiso et al., 2008, 2004). In this study, we investigate how firms' engagement in mandatory CSR activities affects their stock market liquidity. Using the theory of information asymmetry, and social and reputational capital, and linking them to the mandatory CSR regulations via institutional isomorphism, we discuss how CSR activities improve firms' stock market liquidity. In the mandated CSR regulatory context, it becomes compulsory for firms to disclose further information on CSR activities (Ioannou and Serafeim, 2017). In line with the positive theories, mandatory CSR activities and disclosures result in reduced information asymmetry, increased social and reputational capital, and, consequently, improve stock market liquidity of CSR firms.

We provide empirical evidence to this extent by using a shock-based approach with a quasi-natural experiment setup of propensity score matched difference-in-differences and multivariate regression discontinuity design. Using the Indian regulation on mandatory CSR, i.e., the provisions of Section 135 of The Company's Act 2013, our empirical results credibly establish a positive causal link between mandatory CSR activities and stock market liquidity. Our investigation on firm-level actual CSR expenditure data further reveals that CSR firms build up social trust via expenditure in specific projects on education and healthcare. Our study suggests that mandated CSR regulations can redirect a firm to undertake expenditure for the social cause, improve transparency, and reduce information asymmetry, all leading to better stock market liquidity and long-term value creation.

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Table 1: Descriptive statistics

Table 1 reports the mean values of all of the variables (with standard deviations in parentheses in the second row and the number of observations in the third row for each variable) used in this study for the overall sample period (i.e. 2012 to 2017) and also segregated into two periods, i.e., before the enforcement of S-135 (2012-2014) and after the enforcement of S-135 (2015-2017). Panel A reports the statistics for all four liquidity measures i.e, *Amihud* which is Amihud's (2002) illiquidity ratio, *Zeros* the measure from Lesmond et al. (1999), *HL* the high-low spread estimator of Corwin and Schultz (2012). and *FHT* measure from Fong et al. (2017). Panel B reports other firm-level and stock market variables. *Size* is the natural logarithm of total assets, *Leverage* is the ratio of the book value of debt-to-equity, *Cash* is the sum of year-end cash and short term securities scaled by total sales, *CapEx* is capital expenditure scaled by total assets, *IO* is the total percentage of share ownership by institutional investors, *Analyst* is the number of analysts following the stock, *Volatility* is the stock return volatility and *Turnover* is the average daily share turnover. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. Data source: S&P Capital IQ (CIQ) and Centre for Monitoring Indian Economy (CMIE) database.

Panel A: Liquidity measures

Variable	Overall Sample	Pre-S-135 (2012-2014)	Post-S-135 (2015-2017)	Diff	t-stat	p-value
Amihud	8.361	10.288	6.512	-3.776***	-14.60	0.000
	(17.530)	(19.488)	(15.193)			
	18,177	8,898	9,279			
Zeros	0.277	0.281	0.273	-0.007*	-1.69	0.092
	(0.310)	(0.312)	(0.308)			
	18,177	8,898	9,279			
HL	0.125	0.129	0.121	-0.008***	-4.94	0.000
	(0.116)	(0.137)	(0.090)			
	18,177	8,898	9,279			
FHT	0.328	0.338	0.319	-0.019**	-2.09	0.036
	(0.593)	(0.592)	(0.593)			
	17,989	8,803	9,186			

Panel B: Firm level covariates and stock market variables

Variable	Overall Sample	Pre-S-135	Post-S-135	Diff	t-stat	p-value
Size	7.401	7.416	7.387	-0.034	-0.89	0.371
	(2.174)	(2.133)	(2.214)			
	17,733	8,783	8,950			
Leverage	1.012	1.055	0.968	-0.087***	-3.31	0.001
	(1.679)	(1.661)	(1.697)			
	16,106	8,111	7,995			
Cash	0.243	0.247	0.240	-0.007	-0.65	0.515
	(0.116)	(0.137)	(0.090)			
	16,102	7,996	8,106			
CapEx	0.033	0.037	0.030	-0.007***	-8.06	0.000
	(0.593)	(0.592)	(0.593)			
	17,733	8,783	8,950			
IO	31.484	31.893	31.092	-0.801*	-1.85	0.064
	(29.155)	(29.042)	(29.260)			
	18,177	8,898	9,279			
Analyst	1.603	1.673	1.536	-0.137	-1.61	0.107
	(5.739)	(5.989)	(5.488)			
	18,177	8,898	9,279			
Volatility	3.244	2.584	3.878	1.293***	14.66	0.000
	(5.980)	(4.927)	(6.779)			
	18,177	8,898	9,279			
Turnover	0.175	0.151	0.199	0.048***	10.49	0.000
	(0.310)	(0.291)	(0.325)			
	18,177	8,898	9,279			

Table 2: Propensity score matching (PSM)

Panel A of Table 2 reports the t-test of mean differences in covariates between treated and control firms in the pre-S-135 period and Panel B of Table 2 shows a probit model for PSM as per the following specification:

$$Treated_i = \alpha + \boldsymbol{X_{it}}.\boldsymbol{\beta}' + \vartheta_j + \varepsilon_{it}$$

where $Treated_i$ is a categorical variable that takes the value of one if the firm is affected by S-135 and zero otherwise. $\boldsymbol{X_{it}}$ is the vector of covariates used for matching that comprises *Size*, *Leverage*, *Cash*, *CapEx*, and *IO*, all as defined in Table 1. ϑ_j is the industry fixed effects using the Fama-French 17 industries classification. Model [1] presents a probit model predicting the likelihood of being a treated firm from the entire sample of firms with no missing covariates in the pre-S-135 period. Model [2] presents the probit likelihood model for matched treated and comparison firms using PSM with replacement. Heteroskedasticity robust t-stats are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. Data source: CIQ and CMIE database.

Panel A: Mean differences in covariates between treated and control firms in the pre-S135 period

Variable	Control	Treated	Diff (T-C)	t-stat	p-value
Size	6.518	8.245	1.727***	41.46	0.000
	(1.614)	(2.216)			
	4,217	4,566			
Leverage	1.187	0.941	-0.246***	-6.67	0.000
	(1.877)	(1.437)			
	3,772	4,339			
Cash	0.313	0.204	-0.109***	-6.54	0.000
	(0.964)	(0.424)			
	4,069	3,927			
CapEx	0.031	0.042	0.010***	8.06	0.000
	(0.059)	(0.059)			
	4,217	4,566			
IO	23.792	39.261	15.469***	26.03	0.000
	(24.734)	(30.664)			
	4,238	4,660			

Panel B: Pre-match propensity score regression and post-match diagnostic regression

	Dummy = 1 if affected by S-135; 0 if unaffected	
	Pre-match	Post-match
	Model [1]	Model [2]
Size	0.431***	0.002
	(20.06)	(0.06)
Leverage	-0.165***	-0.021
	(-8.11)	(-0.86)
Cash	0.198***	-0.005
	(3.67)	(-0.07)
CapEx	1.817***	0.272
	(3.04)	(0.28)
IO	0.003***	-0.002
	(2.63)	(-1.10)
Constant	-3.163***	0.171
	(-17.45)	(0.70)
Industry FE	Yes	Yes
Pseudo R^2	0.28	0.02
p-value of χ^2	0.00	0.20
Observations	2,679	1,028

Table 3: Univariate difference-in-differences (DiD) estimates

Table 3 reports the univariate difference-in-differences (DiD) estimates between the propensity score matched (PSM) treated and control group firms' stock market liquidity measures, namely *Amihud*, *Zeros*, *HL*, and *FHT*, all as defined in Table 1. The Pre-S-135 period comprises the years 2012-2014, whereas the Post-S-135 period consists of the years 2015-2017. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data source: CMIE database.

Variable	[1]	[2]	[3]	[4]	[5]
		Treated	Control	Diff (T-C)	**DiD**
	Pre-S-135	9.687	11.576	-1.888**	**-2.115****
Amihud				(-1.97)	**(-2.52)**
	Post-S-135	4.348	8.352	-4.003***	
				(-5.01)	
	Pre-S-135	0.236	0.278	-0.043***	**-0.039*****
Zeros				(-2.75)	**(-3.28)**
	Post-S-135	0.187	0.269	-0.082***	
				(-4.71)	
	Pre-S-135	0.140	0.143	-0.004	**-0.042*****
HL				(-0.55)	**(-3.97)**
	Post-S-135	0.140	0.186	-0.046***	
				(-3.74)	
	Pre-S-135	0.412	0.382	0.030	**-0.081****
FHT				(1.33)	**(-2.53)**
	Post-S-135	0.302	0.353	-0.051***	
				(2.25)	

Table 4: Mandated CSR and stock market liquidity: PSM – DiD regression

Table 4 reports the multivariate DiD regression results using the PSM matched treated and control group firms as per the following specification:

$$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm i's stock in year t. $Treated_i$ is an indicator dummy variable that takes the value of one for firms that satisfy at least one of the size thresholds of S-135 and zero otherwise. $After_t$ is a categorical variable that takes the value of one for the post-CSR mandate period (2015-2017) and zero for pre-S-135 period (2012-2014). The DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Amihud	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]
DiD ($\boldsymbol{Treated_i \times After_t}$)	**-2.252*** **	**-0.027** **	**-0.039*** **	**-0.055** **
	(-2.67)	**(-2.42)**	**(-3.51)**	**(-2.16)**
Size	-0.129	-0.022***	-0.002	-0.002
	(-0.67)	(-7.40)	(-0.40)	(-0.31)
Leverage	0.137	0.002	0.000	-0.001
	(0.87)	(0.80)	(0.18)	(-0.21)
Cash	-0.133	0.004	-0.010	0.007
	(-0.26)	(0.63)	(-1.62)	(0.64)
CapEx	-2.261	0.024	-0.032	0.108
	(-0.62)	(0.61)	(-1.29)	(0.93)
IO	0.032	-0.001	0.001	-0.001
	(0.93)	(-1.34)	(1.25)	(-1.02)
Analyst	-0.319**	-0.001	-0.003**	-0.003
	(-2.01)	(-0.45)	(-2.24)	(-0.65)
Volatility	0.080	-0.004***	-0.001	0.003
	(0.85)	(-3.65)	(-1.59)	(0.70)
Turnover	1.477	0.233*	-0.016	-0.185***
	(0.31)	(1.90)	(-1.01)	(-2.79)
Adj. R^2	0.44	0.76	0.49	0.67
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	1,028	1,028	1,028	1,026
Observations	5,912	5,912	5,912	5,874

Table 5: Alternative treated and control groups

Table 5 reports the multivariate DiD regression results using the alternative treated and control group firms as per the following specification:

$$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm *i*'s stock in year *t*. $Treated_i$ is an indicator dummy variable that takes the value of one for firms that do not incur (incur) CSR expenditure in the pre-S-135 (post-S-135) period and zero for firms that do not incur CSR expenditure in both the pre- and post-S-135 periods. $After_t$ is a categorical variable, as defined in Table 4. The DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects, respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Amihud	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]
DiD ($\mathbf{Treated_i} \times \boldsymbol{After_t}$)	**-1.325****	**-0.031*****	**-0.008****	**-0.056*****
	(-2.15)	**(-4.35)**	**(-1.96)**	**(-2.95)**
Size	-0.289	-0.084***	0.019***	-0.025
	(-0.39)	(-6.85)	(4.38)	(-0.95)
Leverage	0.378	0.012***	0.001	-0.010*
	(1.53)	(5.42)	(0.79)	(-1.76)
Cash	-0.417	0.007	-0.008	0.004
	(-0.78)	(1.16)	(-1.58)	(0.43)
CapEx	-1.858	0.029	-0.022	0.185*
	(-0.65)	(0.88)	(-1.27)	(1.95)
IO	-0.057	-0.001**	0.000	-0.002*
	(-1.38)	(-2.15)	(1.31)	(-1.86)
Analyst	-0.094**	0.001*	-0.002***	-0.003
	(-2.12)	(1.74)	(-5.44)	(-1.30)
Volatility	0.073	-0.003***	-0.001***	0.001
	(1.13)	(-4.53)	(-3.18)	(0.19)
Turnover	-3.168**	0.063	-0.023*	0.024
	(-2.44)	(1.13)	(-1.83)	(0.27)
Adj. R^2	0.42	0.82	0.65	0.67
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	1,732	1,732	1,732	1,721
Observations	8,655	8,655	8,655	8,594

Table 6: Alternative liquidity measures: PSM-DiD regression

Table 6 reports the multivariate DiD regression results using the PSM matched treated and control group firms as per the following specification:

$$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by alternative liquidity measures *Amivest* (Amihud et al., 1997), *Zeros2* (Goyenko et al., 2009), *Roll* (Roll, 1984), or *Gamma* (Pástor and Stambaugh, 2003), of firm *i*'s stock in year *t*. $Treated_i$ and $After_t$ are categorical variables, as defined in Table 4. The DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects, respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Amivest	*Zeros2*	*Roll*	*Gamma*
	[1]	[2]	[3]	[4]
DiD ($\boldsymbol{Treated_i} \times \boldsymbol{After_t}$)	**32.550****	**-0.027****	**-0.049*****	**-1.487****
	(2.18)	**(-2.45)**	**(-6.11)**	**(-2.12)**
Size	-0.057	-0.021***	-0.001	-0.042
	(-0.01)	(-7.28)	(-0.41)	(-0.28)
Leverage	-3.574	0.001	-0.001	-0.133
	(-1.20)	(0.75)	(-0.28)	(-0.86)
Cash	17.928	0.004	-0.005	0.640
	(1.53)	(0.64)	(-0.94)	(1.03)
CapEx	78.311	0.026	0.007	-3.283
	(1.28)	(0.68)	(0.19)	(-1.48)
IO	-0.206	-0.001	0.000	0.000
	(-0.49)	(-1.34)	(0.35)	(0.01)
Analyst	19.019**	-0.001	-0.006***	0.058
	(2.17)	(-0.48)	(-3.03)	(0.88)
Volatility	-0.740	-0.004***	-0.001	-0.022
	(-0.60)	(-3.83)	(-0.99)	(-0.71)
Turnover	-30.645	0.193*	-0.038	22.714
	(-0.42)	(1.79)	(-0.91)	(1.48)
Adj. R^2	0.49	0.76	0.35	0.27
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	1,028	1,028	1,028	1,026
Observations	5,912	5,912	5,912	5,841

Table 7: Placebo test

Table 7 reports the multivariate placebo DiD regression results using the PSM matched treated and control group firms as per the following specification:

$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm i's stock in year t. $Treated_i$ is an indicator dummy as defined in Table 4. $After_t$ is a categorical variable that takes the value of one for the false post-shock period (2010-2012) and zero for the false pre-shock period (2007-2009). The placebo DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2007 to 2012. Data sources: CIQ and CMIE database.

	Amihud	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]
DiD ($\boldsymbol{Treated_i} \times \boldsymbol{After_t}$)	-1.766	0.001	-0.003	0.031
	(-1.62)	(0.16)	(-0.79)	(1.00)
Size	-0.561***	-0.014***	0.003***	-0.039***
	(-2.83)	(-6.11)	(2.86)	(-4.28)
Leverage	0.778	0.004*	-0.001	0.018**
	(1.58)	(1.88)	(-1.05)	(2.23)
Cash	0.967	0.012	0.000	0.001
	(0.49)	(1.36)	(0.09)	(0.06)
CapEx	-0.233	-0.059***	0.022*	0.129
	(-0.05)	(-2.72)	(1.71)	(1.45)
IO	0.018	-0.000	0.000	0.001
	(0.71)	(-0.14)	(1.10)	(1.04)
Analyst	-1.014***	0.005***	-0.006***	0.001
	(-5.56)	(2.86)	(-5.80)	(0.10)
Volatility	0.097	-0.003***	0.000	0.005
	(0.85)	(-4.53)	(0.85)	(0.99)
Turnover	1.264**	0.041	0.011	-0.252**
	(2.05)	(0.79)	(0.82)	(-2.13)
Adj. R^2	0.38	0.78	0.54	0.54
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	920	920	920	918
Observations	5,071	5,071	5,071	5,049

Table 8: Multivariate regression discontinuity design (MRDD) estimates

Table 8 reports the regression estimates as per the following specification:

$$SML_{it} = \alpha + \lambda.S135_i + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \vartheta_j + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm *i*'s stock in year *t*. $S135_i$ is a dummy variable that takes the value of one if $BScore_i \geq 0$ and zero if $BScore_i < 0$. $BScore_i$ is the binding score that takes the minimum (nearest to zero) of the three rating variables (net worth of INR 5 billion or more, sales of INR 10 billion or more, or net profit of INR 50 million or more) centered on zero. $BScore_i$ is restricted to a maximum bandwidth of 50% (i.e., ±0.5). $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. ϑ_j is the industry fixed effects using the Fama-French 17 industry classification. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2015 to 2016. Data sources: CIQ and CMIE database.

	Amihud	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]
S135	**-2.074****	**-0.035*****	**-0.048*****	**-0.154****
	(-2.31)	**(-2.65)**	**(-2.59)**	**(-2.01)**
Size	-2.049***	-0.038***	0.022***	-0.128***
	(-6.26)	(-6.45)	(4.77)	(-5.82)
Leverage	0.422*	0.009**	-0.011**	0.042***
	(1.85)	(2.29)	(-2.45)	(2.69)
Cash	0.730	0.006	0.004	0.238
	(0.52)	(0.54)	(0.58)	(1.31)
CapEx	6.420	-0.033	-0.196**	0.666
	(0.78)	(-0.32)	(-2.41)	(0.85)
IO	0.001	-0.000	-0.000**	0.001
	(0.05)	(-0.67)	(-2.12)	(0.84)
Analyst	-0.328**	-0.003**	-0.004***	-0.039***
	(-2.57)	(-2.27)	(-4.00)	(-3.34)
Volatility	0.396***	-0.003***	-0.003***	0.046***
	(3.05)	(-3.58)	(-4.36)	(3.27)
Turnover	0.294*	-0.012***	0.004*	-0.012
	(1.78)	(-3.84)	(1.72)	(-1.14)
Adj. R^2	0.11	0.26	0.05	0.13
Industry FE	Yes	Yes	Yes	Yes
No. of Firms	820	820	820	818
Observations	1,211	1,211	1,211	1,207

Table 9: Cross-sectional heterogeneity

Table 9 reports the multivariate PSM-DiD regression results using the subsample of firms (as indicated) as per the following specification:

$$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, as defined in Table 1, of firm *i*'s stock in year *t*. $Treated_i$ and $After_t$ are categorical variables, as defined in Table 4. The DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects, respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Business Group Affiliation		*Promoter Ownership*		*Institutional Ownership*		*Foreign Sales*		*Geographic Location*	
	Yes	*No*	*High*	*Low*	*High*	*Low*	*Yes*	*No*	*Single*	*Multiple*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
DiD	-1.092	**-2.845*** **	**-2.309** **	-1.890	-0.809	**-3.205** **	**-2.553** **	-1.374	-1.968	**-2.311** **
($Treated_i \times After_t$)	(-0.82)	**(-2.63)**	**(-2.31)**	(-1.07)	(-0.76)	**(-2.51)**	**(-2.44)**	(-0.91)	(-1.11)	**(-2.41)**
Size	-0.233	-0.132	0.194	-0.519*	0.687*	-0.464**	-0.416	0.062	-0.175	-0.140
	(-0.36)	(-0.61)	(0.54)	(-1.78)	(1.67)	(-2.04)	(-0.90)	(0.25)	(-0.34)	(-0.75)
Leverage	-0.082	0.368	-0.005	0.483	-0.220	0.599*	0.274	-0.059	0.257	0.120
	(-0.41)	(1.59)	(-0.03)	(1.40)	(-1.36)	(1.90)	(1.36)	(-0.19)	(0.99)	(0.64)
Cash	0.329	-0.399	0.364	-1.642***	1.210	-1.253*	-0.715	-0.161	-0.543	-0.013
	(0.35)	(-0.64)	(0.51)	(-2.94)	(1.59)	(-1.83)	(-0.75)	(-0.27)	(-0.81)	(-0.02)
CapEx	-3.005	-2.448	-1.513	-5.014	2.723	-8.247	-3.933	0.517	5.397	-4.996
	(-0.48)	(-0.55)	(-0.35)	(-1.00)	(0.64)	(-1.32)	(-0.81)	(0.09)	(0.74)	(-1.19)
IO	-0.071	0.093**	0.047	-0.001	0.023	0.001	0.053	0.023	0.182**	-0.002
	(-1.15)	(2.32)	(0.98)	(-0.01)	(0.55)	(0.03)	(1.55)	(0.36)	(2.35)	(-0.05)
Analyst	-0.140	-0.365	-0.321*	-0.287	-0.460**	-0.229	-0.062	-1.087**	-0.401	-0.262
	(-0.76)	(-1.61)	(-1.70)	(-0.94)	(-2.50)	(-0.56)	(-0.36)	(-2.43)	(-1.12)	(-1.44)
Volatility	0.316**	-0.003	0.096	-0.199	0.195*	-0.219*	-0.127	0.459**	0.000	0.104
	(2.06)	(-0.02)	(0.92)	(-1.35)	(1.67)	(-1.75)	(-1.36)	(2.53)	(0.00)	(1.03)
Turnover	-0.691***	1.542	-5.343***	17.62***	-3.864***	2.263	-0.763***	1.767	11.01*	-4.415***
	(-2.95)	(0.33)	(-3.14)	(12.73)	(-2.70)	(0.40)	(-3.65)	(0.37)	(1.95)	(-2.95)
Adj. R^2	0.56	0.39	0.47	0.26	0.54	0.37	0.46	0.41	0.39	0.46
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	315	750	829	341	540	641	643	665	262	766
Observations	1,783	4,129	4,506	1,406	2,769	3,143	3,094	2,818	1,519	4,393

Table 10: Actual CSR expenditure and stock market liquidity

Table 10 reports the regression estimates as per the following specification:

$$SML_{it} = \alpha + \omega.\boldsymbol{CSR_{it}} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta}' + \vartheta_j + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm *i*'s stock in year *t*. Depending on the model, $\boldsymbol{CSR_{it}}$ is either the natural logarithm of total CSR expenditure or a vector of different types of CSR expenditure scaled by total CSR expenditure of firm *i* in year *t*. $\boldsymbol{X_{it-1}}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. ϑ_j and τ_t are industry and year fixed effects, respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2015 to 2017. Data sources: CSR portal of Indian Ministry of corporate affairs, CIQ, and CMIE database.

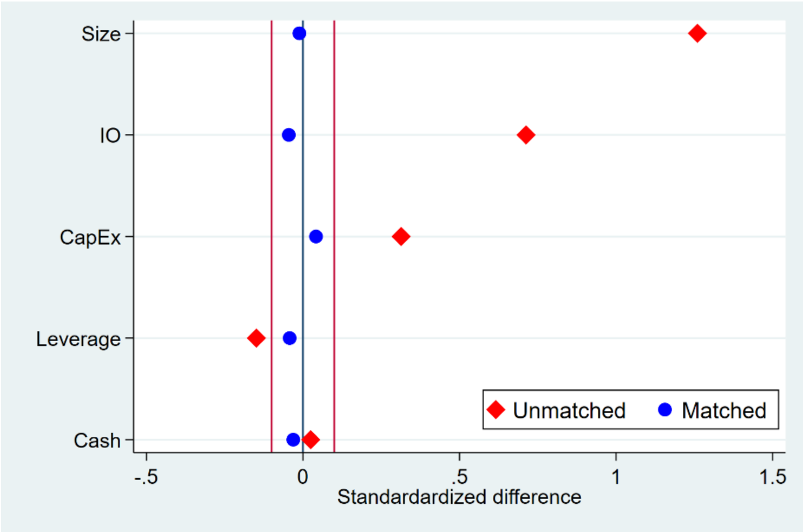
	Total CSR Expenditure				*CSR Expenditure Heterogeneity*			
	Amihud	*Zeros*	*HL*	*FHT*	*Amihud*	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
CSR	**-2.623*** **	**-0.048*** **	**-0.010*** **	**-0.066*** **	-	-	-	-
	(-6.50)	**(-8.75)**	**(-4.31)**	**(-3.28)**				
EDU	-	-	-	-	**-2.767*** **	**-0.120*** **	**-0.010** **	**-0.045*** **
					(-2.75)	**(-10.19)**	**(-2.19)**	**(-2.65)**
HLTH	-	-	-	-	**-5.488*** **	**-0.094*** **	**-0.015** **	**-0.052** **
					(-5.73)	**(-4.12)**	**(-2.35)**	**(-2.31)**
SOC	-	-	-	-	-2.170	**-0.096*** **	-0.007	0.007
					(-1.22)	**(-4.83)**	(-0.89)	(0.15)
ENV	-	-	-	-	-2.579	**-0.084** **	-0.025	-0.047*
					(-0.99)	**(-2.42)**	(-1.57)	(-1.78)
Size	-1.313***	-0.070***	0.022***	-0.024***	-1.473***	-0.072***	0.021***	-0.009***
	(-6.11)	(-16.02)	(12.81)	(-3.73)	(-6.80)	(-16.60)	(12.83)	(-2.68)
Leverage	0.432*	0.008**	-0.003*	0.019**	0.478*	0.007**	-0.003*	0.004**
	(1.70)	(2.42)	(-1.84)	(2.01)	(1.87)	(2.18)	(-1.73)	(2.14)
Cash	2.292**	0.020*	-0.003	0.077**	2.367**	0.019*	-0.003	0.016
	(2.45)	(1.73)	(-0.70)	(2.24)	(2.53)	(1.67)	(-0.64)	(1.35)
CapEx	1.349	-0.356***	0.005	0.289	-0.379	-0.348***	-0.002	0.145
	(0.23)	(-3.89)	(0.14)	(1.05)	(-0.06)	(-3.83)	(-0.04)	(0.82)
IO	0.021	-0.001**	0.000	0.001	0.020	-0.001**	0.000	0.000
	(1.38)	(-2.07)	(0.51)	(1.01)	(1.34)	(-1.98)	(0.50)	(0.67)
Analyst	-0.580*	0.012***	-0.006***	-0.061***	-1.138***	0.004	-0.008***	-0.020***
	(-1.93)	(4.18)	(-6.65)	(-3.41)	(-3.27)	(1.38)	(-8.83)	(-3.05)
Volatility	0.765***	-0.006***	-0.002***	0.060***	0.734***	-0.006***	-0.002***	0.019***
	(5.29)	(-6.56)	(-6.69)	(10.52)	(5.02)	(-6.48)	(-7.13)	(4.48)
Turnover	-0.097	-0.012***	0.001	-0.011*	-0.112	-0.012***	0.000	-0.002
	(-0.59)	(-4.29)	(0.38)	(-1.76)	(-0.68)	(-4.21)	(0.33)	(-0.80)
Adj. R^2	0.13	0.45	0.18	0.26	0.13	0.46	0.17	0.25
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	1,028	1,028	1,028	1,026	1,028	1,028	1,028	1,026
Observations	2,923	2,923	2,923	2,912	2,923	2,923	2,923	2,912

Table 11: Value implication: Mediation analysis

Table 11 presents the results on the mediation effect of stock market liquidity on the relationship between mandatory CSR (DiD) and firm value. The dependent variable is either Tobin's Q (*Tobin's Q*) (Models 1 to 5) or Market to book (*MB*) ratio (Models 6 to 10) of firm *i* in the lead year *t+1*. $Treated_i$ and $After_t$ are categorical variables, as defined in Table 4. The DiD is the interaction between $Treated_i$ and $After_t$ dummies. The stock market liquidity measures are *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm *i*'s stock in year *t*. Covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Tobin's Q (lead)					*MB (lead)*				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
DiD	**0.184***	**0.178***	**0.179***	**0.177***	**0.180***	**0.358***	**0.337**	**0.346**	**0.338**	**0.348**
($\mathbf{Treated_i} \times \boldsymbol{After_t}$)	**(3.24)**	**(3.12)**	**(3.20)**	**(3.08)**	**(3.17)**	**(2.59)**	**(2.45)**	**(2.51)**	**(2.43)**	**(2.51)**
Amihud		**-0.003***					**-0.009***			
		(-3.51)					**(-3.39)**			
Zeros			**-0.632***					**-0.757***		
			(-6.30)					**(-2.96)**		
HL				**-0.207***					**-0.478**	
				(-3.04)					**(-2.37)**	
FHT					**-0.054***					**-0.076**
					(-3.34)					**(-2.29)**
Size	-0.120**	-0.123**	-0.151***	-0.119**	-0.121**	0.056*	0.050	0.047	0.052	0.056*
	(-2.32)	(-2.35)	(-2.85)	(-2.29)	(-2.33)	(1.67)	(1.48)	(1.42)	(1.53)	(1.66)
Leverage	-0.008	-0.008	-0.006	-0.008	-0.008	0.127**	0.128**	0.129**	0.127**	0.127**
	(-1.17)	(-1.15)	(-0.91)	(-1.19)	(-1.23)	(2.49)	(2.51)	(2.53)	(2.49)	(2.50)
Cash	0.031	0.029	0.033	0.029	0.030	0.045	0.038	0.048	0.041	0.047
	(1.06)	(0.98)	(1.12)	(1.00)	(1.02)	(0.71)	(0.59)	(0.75)	(0.64)	(0.74)
CapEx	-0.080	-0.067	-0.113	-0.081	-0.092	0.594	0.627	0.537	0.587	0.540
	(-0.42)	(-0.35)	(-0.59)	(-0.42)	(-0.48)	(0.89)	(0.94)	(0.81)	(0.88)	(0.81)
IO	0.003	0.003	0.003	0.003	0.003	0.003	0.004	0.003	0.004	0.003
	(1.44)	(1.47)	(1.29)	(1.47)	(1.43)	(0.48)	(0.52)	(0.42)	(0.49)	(0.48)
Analyst	0.067**	0.067**	0.071**	0.066**	0.064**	0.030	0.029	0.034	0.029	0.026
	(2.34)	(2.32)	(2.48)	(2.31)	(2.25)	(0.48)	(0.46)	(0.54)	(0.46)	(0.42)
Volatility	0.051***	0.051***	0.046***	0.051***	0.053***	0.089***	0.089***	0.083***	0.090***	0.094***
	(7.64)	(7.68)	(6.84)	(7.66)	(8.09)	(4.48)	(4.54)	(4.07)	(4.51)	(4.68)
Turnover	0.035	0.030	-0.001	0.030	0.033	-0.034	-0.053	-0.079	-0.047	-0.038
	(0.62)	(0.52)	(-0.02)	(0.52)	(0.57)	(-0.23)	(-0.36)	(-0.54)	(-0.31)	(-0.26)
Adj. R^2	0.72	0.72	0.73	0.72	0.72	0.52	0.52	0.52	0.52	0.52
Sobel test (p-value)	-	<0.01	<0.01	<0.01	<0.01	-	<0.01	<0.01	<0.05	<0.05
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	997	997	997	997	997	1,026	1,026	1,026	1,026	1,026
Observations	5,485	5,485	5,485	5,485	5,485	5,774	5,774	5,774	5,774	5,774

Figure 1: Pre- and post-matched firms' mean differences in covariates



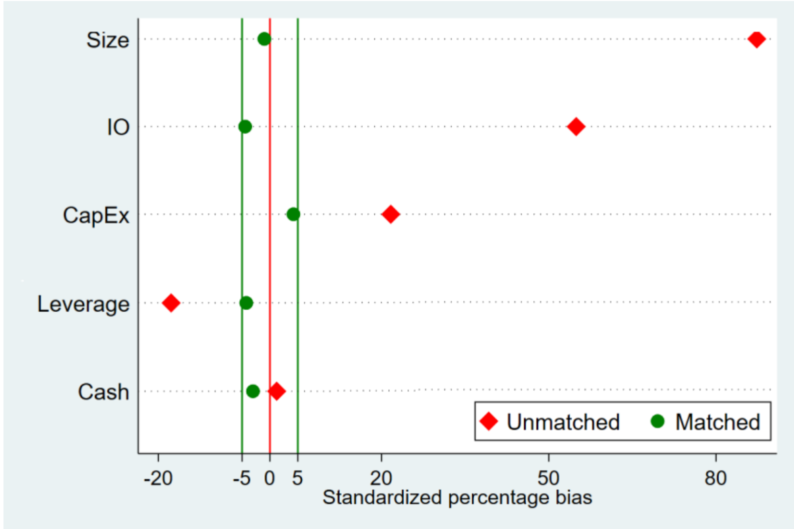
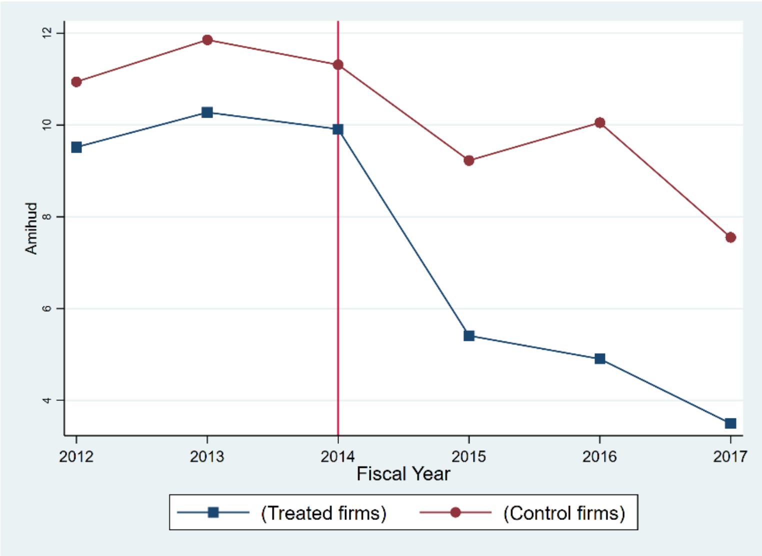


Figure 1a shows the z-score of the covariates *Cash*, *Leverage*, *CapEx*, *IO*, and *Size* of the treated and control group firms before and after PSM. We observe very high z-scores pre-matching (unmatched), indicating significant differences among treated and control firms. The z-scores post-matching (matched) is close to zero indicating that there is no significant difference between treated and control firms. The sample period for matching ranges from 2012 to 2014, which is the period before the introduction of CSR mandate reform. Data source: CMIE database.

Figure 1b shows the standardized percentage bias of the covariates *Cash*, *Leverage*, *CapEx*, *IO*, and *Size* of the treated and control group firms before and after PSM. We observe very high bias pre-matching (unmatched), indicating significant differences among treated and control firms. The bias post-matching (matched), is close to zero indicating that there is no significant difference between treated and control firms. The sample period for matching ranges from 2012 to 2014, which is the period before the introduction of CSR mandate reform. Data source: CMIE database.

Figure 2: Parallel trend plots



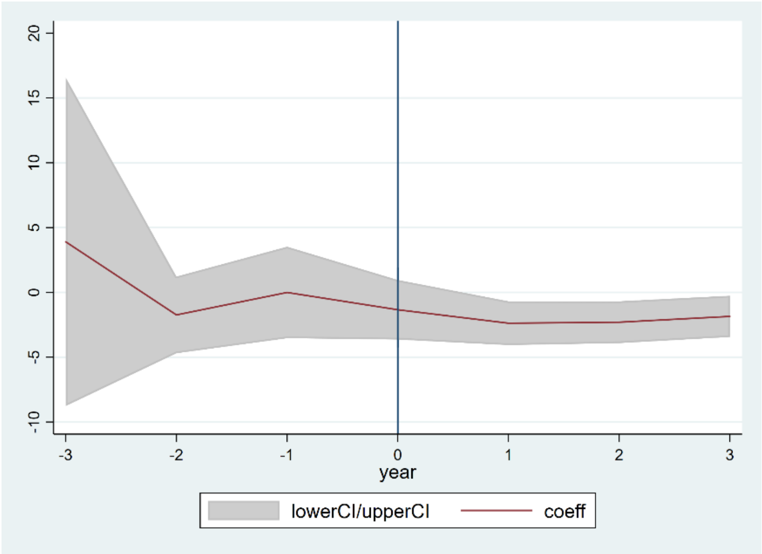


Figure 2a shows parallel trend of the liquidity measure (*Amihud*) of the treated and the control group firms in the pre- and post-S-135 regulation. It can be seen that pre-S-135, the mean liquidity measures of both treated and control group forms follow a parallel trend, and in the post-S-135 the individual trends diverge. Data source: CMIE database

Figure 2b shows the trend of the DiD coefficient for the liquidity measure (*Amihud*), and we can see that the coefficient estimate moves around zero and is insignificant as shown by the wide confidence interval (CI) and in the pre-S-135 period, whereas in the post-S-135 the DiD coefficient is significantly lower than zero with a very narrow CI. Data source: CMIE database.

Figure 3: MRDD plots for liquidity measures

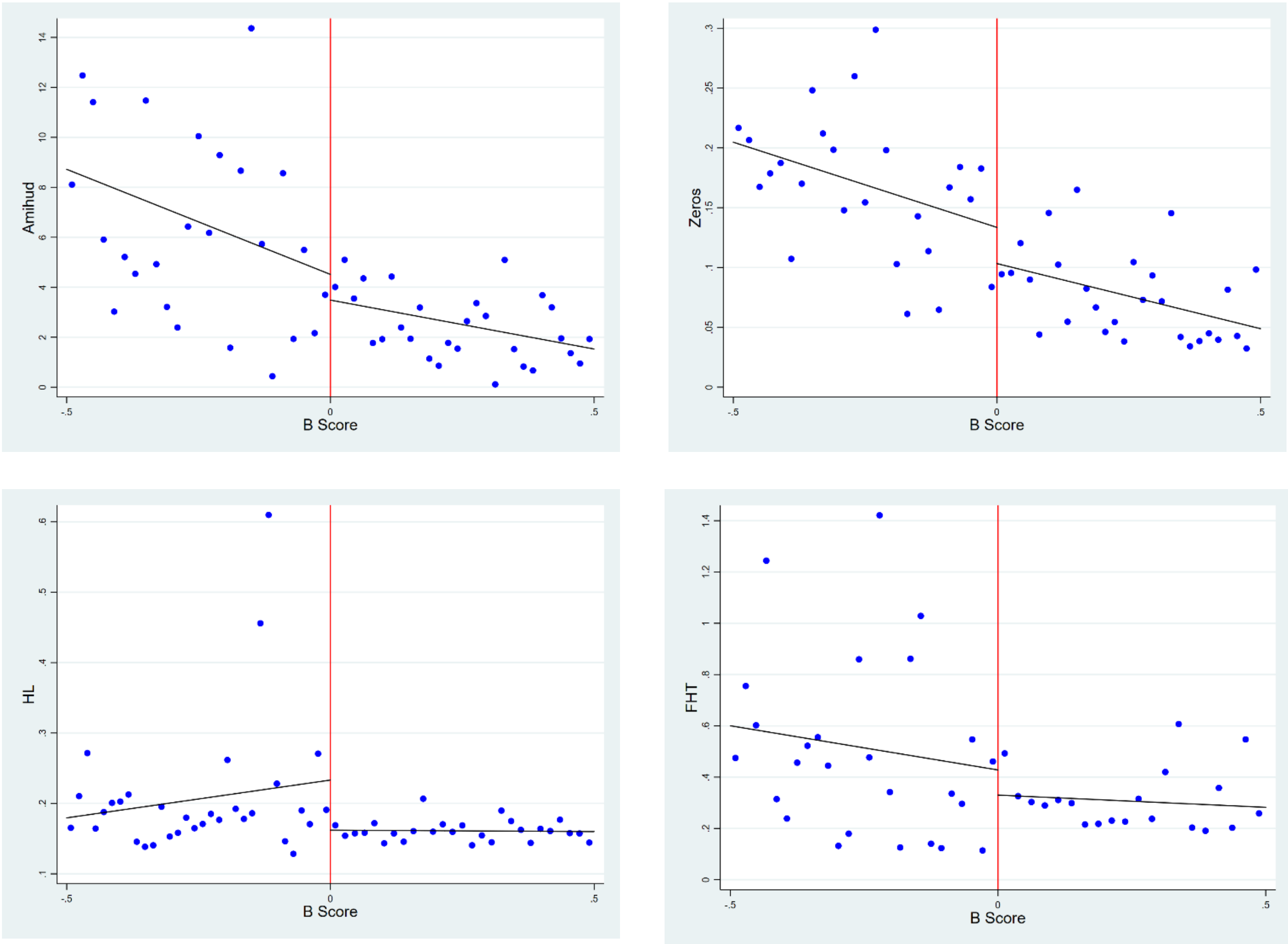


Figure 3 shows the Multivariate regression discontinuity (MRDD) plots for the four stock market liquidity measures (*Amihud, Zeros, HL, and FHT*) around the running variable B Score with maximum bandwidth to 50% (i.e., ±0.5). Data source: CMIE database.

APPENDIX

Table A1: Variable description and sources

Variable	Description	Source
Liquidity measures		
Amihud	Amihud’s (2002) illiquidity ratio.	Derived from CMIE
Zeros	Zeros spread measure of Lesmond et al. (1999)	Derived from CMIE
HL	High-low spread measure of Corwin and Schultz (2012)	Derived from CMIE
FHT	FHT spread measure of Fong et al. (2017)	Derived from CMIE
Key DiD and MRDD variables		
Treated	Indicator variable that takes the value of one if it satisfies any one of the thresholds of S-135 and zero otherwise	Derived from CMIE
After	Indicator variable that takes the value of one for the years 2015-2017 and zero otherwise	Derived from CMIE
S135	For MRDD analysis, takes the value of one if *BScore* ≥ 0 and zero if *BScore* < 0.	Derived from CMIE
Covariates		
Size	Natural logarithm of total assets	Derived from CMIE
Leverage	The ratio of the book value of debt-to-equity	CMIE
Cash	Sum of year-end cash and short-term securities scaled by total sales	Derived from CMIE
CapEx	Annual additions to property, plant, and equipment scaled by total assets	Derived from CMIE
IO	Total percentage of share ownership held by institutional investors	CMIE
Stock market characteristics		
Analyst	Number of analysts following the stock	S&P Capital IQ
Volatility	The annual average of daily stock return volatility	Derived from CMIE
Turnover	The annual average of daily share turnover	Derived from CMIE

Table A2: Controlling for reputation

Table A2 reports the multivariate DiD regression results using the PSM matched treated and control group firms as per the following specification:

$$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm *i*'s stock in year *t*. $Treated_i$ and $After_t$ are categorical variables, as defined in Table 4. The DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, *IO*, *Goodwill* (taken as firm's goodwill scaled by total assets), and *Age* (taken as the natural logarithm of firm age in years), and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects, respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Amihud	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]
DiD ($\mathbf{Treated_i} \times \boldsymbol{After_t}$)	**-2.233*** **	**-0.025** **	**-0.039*** **	**-0.056** **
	(-2.63)	**(-2.16)**	**(-3.53)**	**(-2.19)**
Size	-0.184	-0.031***	-0.002	0.001
	(-0.79)	(-7.69)	(-0.36)	(0.14)
Leverage	0.137	0.002	0.000	-0.001
	(0.87)	(0.84)	(0.18)	(-0.23)
Cash	-0.139	0.003	-0.010	0.007
	(-0.27)	(0.53)	(-1.61)	(0.63)
CapEx	-2.226	0.028	-0.032	0.107
	(-0.61)	(0.71)	(-1.29)	(0.93)
IO	0.032	-0.001	0.001	-0.001
	(0.93)	(-1.37)	(1.25)	(-1.01)
Analyst	-0.317**	-0.001	-0.003**	-0.003
	(-1.99)	(-0.44)	(-2.24)	(-0.62)
Volatility	0.081	-0.004***	-0.001	0.003
	(0.86)	(-3.57)	(-1.60)	(0.69)
Turnover	1.435	0.227*	-0.016	-0.187***
	(0.30)	(1.92)	(-1.02)	(-2.84)
Goodwill	-16.85	0.972	-0.009	-2.381
	(-0.22)	(0.51)	(-0.01)	(-0.55)
Age	0.147	0.022***	-0.000	-0.008
	(0.31)	(3.20)	(-0.05)	(-0.56)
Adj. R^2	0.44	0.76	0.49	0.67
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	1,028	1,028	1,028	1,028
Observations	5,912	5,912	5,912	5,874

Table A3: Treated firms without extraordinary events

Table A3 reports the multivariate PSM-DiD regression results without the treated firms subjected to extraordinary events in the post-S-135 period:

$$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm *i*'s stock in year *t*. $Treated_i$ and $After_t$ are categorical variables, as defined in Table 4. The DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects, respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Amihud	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]
DiD ($\mathbf{Treated_i} \times \boldsymbol{After_t}$)	**-2.172****	**-0.027****	**-0.037*****	**-0.060****
	(-2.47)	**(-2.33)**	**(-3.34)**	**(-2.33)**
Size	-0.156	-0.022***	-0.000	-0.002
	(-0.81)	(-7.25)	(-0.02)	(-0.32)
Leverage	0.168	0.002	0.000	-0.001
	(1.01)	(0.93)	(0.13)	(-0.28)
Cash	-0.236	0.004	-0.011*	0.003
	(-0.44)	(0.64)	(-1.77)	(0.34)
CapEx	-1.829	0.036	-0.041	0.065
	(-0.49)	(0.91)	(-1.57)	(0.58)
IO	0.027	-0.000	0.001**	-0.002
	(0.73)	(-1.05)	(2.07)	(-1.47)
Analyst	-0.355**	-0.002	-0.003***	-0.004
	(-2.06)	(-0.68)	(-2.63)	(-0.61)
Volatility	0.095	-0.004***	-0.001*	0.005
	(0.97)	(-3.36)	(-1.65)	(0.95)
Turnover	1.488	0.235*	-0.010	-0.205***
	(0.31)	(1.91)	(-0.57)	(-2.69)
Adj. R^2	0.44	0.76	0.51	0.68
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	966	966	966	966
Observations	5,551	5,551	5,551	5,515

Table A4: Alternative PSM-DiD

Table A4 reports the multivariate PSM-DiD regression results using the alternative treated and control group firms as per the following specification:

$$SML_{it} = \alpha + \beta.(Treated_i \times After_t) + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm i's stock in year t. $Treated_i$ is an indicator dummy variable that takes the value of one for firms that do not incur (incur) CSR expenditure in the pre-S-135 (post-S-135) period and zero for firms that do not incur CSR expenditure in both the pre- and post-S-135 periods. $After_t$ is a categorical variable, as defined in Table 4. The DiD is the interaction between $Treated_i$ and $After_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. γ_i and τ_t are the firm and year fixed effects, respectively. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The overall sample period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Amihud	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]
DiD ($\mathbf{Treated_i} \times After_t$)	**-2.578*** **	**-0.041*** **	**-0.033*** **	**-0.073*** **
	(-2.88)	**(-3.21)**	**(-3.07)**	**(-2.60)**
Size	-0.169	-0.024***	-0.001	-0.009
	(-0.71)	(-6.14)	(-0.10)	(-1.19)
Leverage	0.189	0.002	0.000	-0.003
	(0.85)	(0.92)	(0.13)	(-0.76)
Cash	-0.224	0.004	-0.010	0.011
	(-0.44)	(0.42)	(-1.15)	(0.87)
CapEx	-6.038	0.009	-0.045	0.066
	(-1.31)	(0.18)	(-1.32)	(0.42)
IO	-0.048	-0.001	0.000	-0.003*
	(-1.17)	(-1.47)	(0.33)	(-1.74)
Analyst	-0.455**	-0.001	-0.004**	-0.003
	(-2.07)	(-0.41)	(-2.05)	(-0.44)
Volatility	0.099	-0.004**	-0.000	0.005
	(0.75)	(-2.22)	(-0.41)	(0.73)
Turnover	3.755	0.152	-0.023	-0.256***
	(0.65)	(1.08)	(-1.63)	(-2.69)
Adj. R^2	0.43	0.76	0.52	0.68
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	649	649	649	649
Observations	3,692	3,692	3,692	3,662

Table A5: CSR expenditure under different project categories

Panel A: CSR expenditure under various development sectors allowed under S-135

Code	Development sector	Expenditure (in INR billion)
D1	Agro-Forestry	1.0681
D2	Animal Welfare	0.3009
D3	Armed Forces, Veterans, War Widows/ Dependents	0.3308
D4	Art and Culture	4.1
D5	Clean Ganga Fund	0.0071
D6	Conservation of Natural Resources	1.1194
D7	Education	58.5953
D8	Environmental Sustainability	17.3801
D9	Gender Equality	1.6615
D10	Health Care	39.4831
D11	Livelihood Enhancement Projects	5.0384
D12	NEC/ Not Mentioned	9.7112
D13	Other Central Government Funds	6.9735
D14	Poverty, Eradicating Hunger, Malnutrition	11.781
D15	Prime Ministers National Relief Fund	1.6502
D16	Provision of blood units to thalassemia patient	0.0047
D17	Rural Development Projects	18.5818
D18	Safe Drinking Water	1.9433
D19	Sanitation	7.6775
D20	Senior Citizens Welfare	0.1234
D21	Setting Up Orphanage	0.135
D22	Setting up homes and hostels for women	0.4076
D23	Slum Area Development	1.2627
D24	Socio-Economic Inequalities	1.0077
D25	Special Education	0.7406
D26	Swachh Bharat Kosh	2.5799
D27	Technology Incubators	0.2049
D28	Training to Promote Sports	1.9003
D29	Vocational Skills	5.5467
D30	Women Empowerment	1.4173
	Total	**202.734**

Panel B: Reclassification of development sector CSR expenditure into CSR activities for the study

CSR activity	Code	Expenditure (in INR billion)
Education and Training (*EDU*)	D7, D25, D27, D28, D29	66.9878
Healthcare (*HLTH*)	D10, D14, D16, D18, D19	60.8896
Social justice and welfare (*SOC*)	D3, D4, D9, D11, D13, D15, D17, D20, D21, D22, D23, D24, D30	42.6899
Environment (*ENV*)	D1, D2, D5, D6, D8, D26	22.4555
NEC/ Not Mentioned	D12	9.7112
Total		**202.734**

Mandatory CSR Expenditure and Stock Market Liquidity

Internet Appendix

This internet appendix contains the empirical results relating to Section 6.4, footnote 30 of the article.

CSR expenditure and stock liquidity: PSM shock IV design

Since expenditure on CSR under S-135 is "comply or explain" basis, an issue could be raised that some of the mandated firms may choose to spend on CSR activities whereas others may choose to explain non-compliance. Thus, our estimates from specification (11) in the paper could be subjected to the self-selection bias issue. However, this is very unlikely as mandated firms must provide a convincing reason and offer reasonable justification if they are incapable of expending the recommended amount in CSR (Dharmapala and Khanna, 2018). Moreover, firms must spend the specified amount in the Ministry of Corporate Affairs authorized CSR activities only. Nevertheless, to remove any doubt of self-selection bias and to improve confidence in our results, we take an exogenous shock-based instrumental variable (IV) approach following Iliev (2010).

S-135 came into effect from the beginning of the 2015 fiscal year. Hence, companies were unsure whether S-135 would pass in the parliament in 2014. As a result, firms that were already satisfying any of the thresholds of S-135 in 2014 most likely fell under the provisions of S-135 in the fiscal year 2015 and had to spend on mandatory CSR activities. Thus, following Iliev (2010), we define our IV as an indicator variable ($Treated_{2014}$) that takes the value of one for those firms that satisfied any of the thresholds of S-135 in the fiscal year 2014 and zero otherwise. Next, we run the 2SLS IV regression on the cross-section of PSM matched treated and control firms for the two years post-S-135 (i.e., FY ending 2015 and 2016). We run our IV regression on the PSM-matched sample to ensure that our shock IV design does not suffer from pre-treatment balance issues (Atanasov and Black, 2021). For our PSM shock IV design, we estimate the following 2SLS model:

$$\boldsymbol{CSR_{it}} = \alpha + \lambda . Treated_{2014} + \boldsymbol{X_{it-1}} . \boldsymbol{\delta}' + \vartheta_j + \varepsilon_{it}$$
$$SML_{it} = \alpha + \omega . \widehat{\boldsymbol{CSR_{it}}} + \boldsymbol{X_{it-1}} . \boldsymbol{\delta}' + \vartheta_j + \varepsilon_{it} \quad (1)$$

where $\boldsymbol{CSR_{it}}$ is the natural logarithm of total CSR expenditure of firm *i* in year *t*. $Treated_{2014}$ is an indicator variable that takes the value of 1 if firm *i* met any of the thresholds of S-135 in the fiscal year 2014 and zero otherwise. SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in section 4.1 of the paper of firm *i* in year *t*. $\boldsymbol{X_{it-1}}$ is a vector of one-year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO* and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in 4.3 of the paper. ϑ_j controls for industry fixed effects.

We present the results from our PSM shock IV regressions in Table IA1. Model [1] shows the first-stage estimates. As expected, we find that our IV ($Treated_{2014}$) is significantly positively associated with $\boldsymbol{CSR_{it}}$. Models [2] to [5] show the second stage of the IV estimates. We find that there is a negative and generally significant (at least at the 5% level) association between fitted $\widehat{\boldsymbol{CSR_{it}}}$ and the stock market liquidity proxies. Overall, our PSM shock IV results mitigate any issue of self-selection bias of our main results from specification (11) in the main paper and provide further robustness.

References

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Dharmapala, D., Khanna, V., 2018. The impact of mandated corporate social responsibility: Evidence from India's Companies Act of 2013. Int. Rev. Law Econ. 56, 92–104. https://doi.org/10.1016/j.irle.2018.09.001

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Table IA1: Actual CSR expenditure and stock market liquidity: PSM shock IV

Table IA1 reports the instrumental variable (IV) 2SLS regression estimates as per the following specification:

$$\boldsymbol{CSR_{it}} = \alpha + \lambda.Treated_{2014} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta}' + \vartheta_j + \varepsilon_{it}$$

$$SML_{it} = \alpha + \omega.\widehat{\boldsymbol{CSR_{it}}} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta}' + \vartheta_j + \varepsilon_{it}$$

where SML_{it} is the stock market liquidity, proxied by *Amihud*, *Zeros*, *HL*, or *FHT*, all as defined in Table 1, of firm *i*'s stock in year *t*. $\boldsymbol{CSR_{it}}$ is the natural logarithm of total CSR expenditure of firm *i* in year *t*. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged covariates that include *Size*, *Leverage*, *Cash*, *CapEx*, and *IO*, and stock market variables that consist of *Analyst*, *Volatility*, and *Turnover*, all as defined in Table 1. ϑ_j is industry fixed effects. In the first stage [Model 1], $\boldsymbol{CSR_{it}}$ is regressed on the IV (*Treated₂₀₁₄*), which is an indicator variable that takes the value of 1 if firm *i* met any of the thresholds of S-135 in the fiscal year 2014 and zero otherwise, alongside other covariates and industry fixed effects. Models [2] to [5] present the second stage of the IV estimates (The effect of fitted $\widehat{\boldsymbol{CSR_{it}}}$ on stock market liquidity with all covariates and industry fixed effects included). Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2015 to 2016. Data sources: CSR portal of Indian Ministry of corporate affairs, CIQ, and CMIE database.

	First-Stage	*Second-Stage*	*Second-Stage*	*Second-Stage*	*Second-Stage*
	CSR	*Amihud*	*Zeros*	*HL*	*FHT*
	[1]	[2]	[3]	[4]	[5]
CSR		**-8.572*****	**-0.097*** **	**-0.047*** **	**-0.116** **
		(-5.67)	**(-4.48)**	**(-2.74)**	**(-2.06)**
Size	0.139***	-0.689**	-0.062***	0.028***	-0.019**
	(13.92)	(-2.29)	(-11.69)	(3.97)	(-2.13)
Leverage	-0.050***	0.020	0.005	-0.008**	0.013
	(-3.99)	(0.07)	(1.28)	(-2.10)	(1.25)
Cash	-0.037**	1.927**	0.012	-0.005	0.073**
	(-2.01)	(2.03)	(1.09)	(-0.78)	(2.10)
CapEx	1.963***	9.955	-0.227**	-0.011	0.335
	(4.76)	(1.33)	(-2.06)	(-0.15)	(1.08)
IO	-0.001	0.006	-0.001**	-0.000	0.000
	(-0.58)	(0.35)	(-2.03)	(-0.66)	(0.45)
Analyst	0.264***	1.293**	0.028***	0.004	-0.043*
	(8.06)	(2.56)	(3.80)	(0.91)	(-1.83)
Volatility	0.030***	1.145***	-0.005***	-0.002***	0.071***
	(5.09)	(6.72)	(-3.74)	(-2.86)	(10.79)
Turnover	0.017**	-0.013	-0.012***	0.002	-0.010
	(2.55)	(-0.06)	(-4.16)	(0.74)	(-1.51)
Treated₂₀₁₄	0.620***				
	(13.97)				
Adj. R^2	0.49	-	-	-	-
Industry FE	Yes	Yes	Yes	Yes	Yes
First-Stage F	195.2	-	-	-	-
Observations	1,999	1,999	1,999	1,999	1,991