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Saved by the bell? Equity market responses to surprise Covid-19 lockdowns and central bank interventions

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March 2022

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Keywords: Covid-19; event study; earnings calls; firm performance; uncertainty; central bank policies

JEL Code: G14; G18; G32; E58; L25; D8

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1 Introduction

The coronavirus pandemic which started in 2020 inflicted an unprecedented health shock upon countries all over the world. Necessary actions adopted to prevent the spread of the disease (Covid-19) such as social distancing, mobility restrictions and in extreme cases, lockdowns, caused severe economic damage. Globally, the non-financial corporate sector entered the crisis in a more vulnerable position as compared to 2007, in part due to its higher leverage (International Monetary Fund, 2021). These firms came under direct and serious stress due to supply-chain disruptions, collapse in aggregate demand, sudden stops in cash flows, and generally higher uncertainty. In response, governments and central banks announced a plethora of policy actions to help these firms survive the crisis.[1]

In this paper, we investigate the equity market reactions of Indian non-financial firms which had exposure or concern regarding the pandemic early on in 2020, even before it assumed serious proportions in the country. To identify these firms, we use the informational content of earnings call transcripts to gauge a firm's exposure to the pandemic. Using natural language processing techniques, we interpret the mentions of Covid-19 in firms' earnings call reports as an indicator of firm-specific expression of concern about the pandemic.[2] We then study whether firms that discussed the pandemic early on in 2020 were worse affected when large-scale mobility restrictions were announced, compared to their peers who did not discuss the pandemic during the same time. We disentangle the mechanisms that might explain the heterogeneity of observed stock market responses. Finally, we ask whether these same firms benefitted more when the central bank announced relief packages to support the economy and prevent severe losses.

We use India as our case-study for two reasons. The Indian government imposed a nationwide lockdown on 24 March 2020, with a mere four-hour notice, at a time when the total number of cases in the country were less than one thousand (see panel (a), Figure 1). The lockdown in India was regarded as one of the largest and most severe lockdowns in the world at the time, based on data from the Oxford COVID-19 Government Response Tracker (see panel (b), Figure 1). Three days after the lockdown, on 27 March 2020, the Reserve Bank of India (RBI) made an unscheduled monetary policy announcement, which included a policy package to help ameliorate the financial pressure faced by firms as a result of the lockdown. This gives us a unique set up wherein a stringent nationwide lockdown was followed by the announcement of a surprise policy package.

Our approach combines a standard event study methodology with a differences-in-difference analysis. Stock market returns convey useful information about the kind of expectations market participants and investors harbour regarding a firm's future cash flows, and therefore serves as our dependent variable of interest. We first calculate the cumulative abnor-

[1] By mid-March 2021, global pandemic-related fiscal support measures had totalled roughly USD 16 trillion, about 19% of world GDP (International Monetary Fund, 2021).

[2] In this paper we use Covid-19, coronavirus and pandemic, interchangably.

mal returns of the non-financial firms in our sample within a two-day window around the lockdown announcement. While doing so, we account for the market returns which capture the general macroeconomic conditions as well as pandemic-related news and other common shocks. This provides us with an estimate of investors' views on the discounted future impact of the lockdown on the firms. Using a tight window around the event date reduces the likelihood that the results are driven by confounding factors (Gürkaynak and Wright, 2013). Thereafter, using a cross-sectional regression set up, we compare the cumulative abnormal returns of the firms that had early discussions about the pandemic (the "treated" group), relative to their peers who did not (the "control" group). This is informative of whether investors' views on the future impact of the lockdown differed depending on firms' early disclosures. We ensure that we compare firms within the same sector by incorporating sector fixed effects in all our specifications.

We find that "treated" firms, i.e. those firms that discussed the pandemic in their January-February 2020 earnings call reports, and hence in our measure, were *exposed* to the pandemic early on, fared worse in terms of their stock market returns when the 24 March lockdown was announced in India. Across a range of specifications, we find that treated firms had between 3 to 5.5 percentage points lower cumulative abnormal returns as compared to the "control" group, i.e. those firms which did not mention the pandemic in their earnings call reports in early 2020.

Next, we investigate the mechanisms that might explain these differences. For one, it may be that the two groups of firms were fundamentally different from one another in terms of their balance sheet characteristics. We however find that the two groups were broadly similar in terms of their pre-pandemic financial features. At the same time, there may have been systematic differences in investor sensitivity to specific business model characteristics of the firms across these two groups *at the time of the lockdown announcement*, such as cash holdings or foreign exchange revenues. To ensure that our results are not driven by differences in the financial vulnerabilities across firms, in all our specifications we control for pre-existing firm balance sheet characteristics, such as cash holdings, inventories, long and short-term borrowing, profitability, and foreign exchange earnings. The differences in stock market responses continue to remain robust.

It may also be that the treated firms were particularly vulnerable because of their international linkages to specific countries, notably China where the pandemic originated. This could explain why they had lower returns as compared to their peers. To address this concern, we count the non-pandemic related mentions of China in each earnings call report and include that as a regressor in our specification. This is intended to capture normal time supply or demand connections to China for each firm. We find that it does not help explain away the differences across treated and control groups.

Next, we account for the *sentiments* expressed during the discussion of Covid-19 pandemic in the earnings calls. It could be that managers from treated firms were more pessimistic in their outlook, which might explain why investors viewed their stocks negatively during the lockdown announcement. Another source of difference could be the general disruption to international or domestic supply chains faced by the treated firms due to the lockdown announcement, or a higher degree of worry about domestic demand dislocations. To account for this, we include mentions of supply and demand-related words, in the context of the pandemic, in our specifications. We do not find any evidence to support these hypotheses either.

Finally, we investigate whether differences in abnormal stock returns between differently exposed firms could be explained by discussions around *uncertainty induced by the pandemic*. We expect investors to respond negatively to the lockdown announcement especially for firms that expressed concerns around future uncertainty. This is because uncertainty reflects a shock to – or a widening of – the future cash flow distribution (see, for example, Fama, 1990). It reflects ambiguity in how the new information related to the pandemic affects the firm's fundamentals. We therefore check whether uncertainty-related words are mentioned in pandemic-related sentences, and find this to be the case for more than 55% of the treated firms. These firms typically express lack of clarity not just about the future generally, but also the likely impact of the disease on the firm (see Appendix D for a few examples of uncertainty related sentences in the pandemic context). We find that including pandemic-related uncertainty words as an additional control in our regressions explains away the differences between the treated and control firms at the time of the lockdown announcement.

In the last part of our analysis, we examine the impact of an unscheduled monetary policy announcement by the Reserve Bank of India (RBI) just three days after the nation-wide lockdown. This announcement was the biggest surprise in the RBI's history since Inflation Targeting was formally introduced in October 2016 (figure 10). We expect that this policy package was more beneficial for the treated firms, since it dampened the impact of the lockdown shock on their future cash flows. In line with our expectations, we find that this announcement had a favourable impact on firms that discussed early exposure to the pandemic, and it helped in reversing the adverse impact of the lockdown announcement on these firms' stock returns, at least in the short term.

In this paper, we make three crucial contributions. First, since the onset of the pandemic, the literature on how to capture non-financial firms' vulnerabilities to tail risks has grown (for example, Fahlenbrach *et al.*, 2020). Our paper adds a new dimension to this literature by relying on information provided in a timely and spontaneous fashion by firms on how they view their own resilience in the face of such shocks. These voluntary disclosures, which influence investors' views on cash flow uncertainties, are relevant not only at the time of the earnings calls, but also when policy shocks materialise in response to these tail events.

Second, an important theme emerging from the studies on financial fragility in the Covid-19 crisis is how monetary policy interventions have helped stabilize markets (Goldstein *et al.*, 2021). While it is still too early to determine the transmission of stimulus packages to the real economy, it is useful to understand the short-term effectiveness of these interventions. There have been some studies looking at the impact of asset purchase programs in emerging economies during the pandemic, such as Sever *et al.* (2020). We add to this literature by providing evidence on the effectiveness of conventional monetary policy and other tools in mitigating the short-term impact of unexpected crises and providing firms with critical breathing space.

Finally, our textual analysis methodology, which is easily replicable and transparent, shows how earnings call reports can complement traditional analysis as a crucial source of information on firms' own views of the future. It can also be used by regulators as a timely measure of firms' exposure to various tail risks.

The paper is structured as follows. In Section 2, we situate our work within the existing literature and set out the hypotheses. In Section 3, we provide an overview of our data, including the textual analysis used to construct a novel measure of firm-specific exposure to the pandemic. In Section 4, we discuss the event study and cross-sectional regression methodology as well as the identification strategy. We outline the results and a discussion of the various mechanisms in Section 5. Finally, in Section 6, we investigate the impact of the Indian central bank's policy announcement. We conclude in Section 7 and outline possible avenues for future research.

2 Hypothesis development and literature review

Our paper is related to four major strands of the literature, starting more generally from the effects of voluntary disclosures on firm stock market performance, to pandemic-specific investigations into the determinants of firm resilience, impact of central bank interventions, and measuring or predicting firm-specific concerns around tail risks.

The literature that focuses on firms' earnings call reports as a medium of voluntary disclosures finds that they provide additional value-relevant information for stock market returns, trading volumes (Frankel *et al.*, 1999, Bushee *et al.*, 2003, 2004), and options pricing (Borochin *et al.*, 2018). More recently, studies such as Hassan *et al.* (2020), Loughran and McDonald (2020) and Lopatta *et al.* (2020) have used information in earnings call reports to determine firms' experiences with previous health crises and their subsequent capacity for risk-detection. We draw on this literature by using earnings call reports as our main source of information regarding firm disclosures about Covid-19, acknowledging that these disclosures are value-relevant for investors not just at the time of the earnings call, but also at the time when the shock materialises – in the form of a surprise lockdown announcement, in our case. Following this literature, we first show that the earnings call reports of non-financial firms in January-February 2020 provide useful information about firm-specific exposures to the pandemic. We find that the abnormal stock market returns of firms discussing the Covid-19 pandemic, the so-called "treated firms", were *lower* after their earnings calls in January-February 2020 as compared to their peers with no discussions of the pandemic, in line with our expectations.

The paper closest to ours is Hassan *et al.* (2020), which finds that global listed firms with greater exposure to previous disease outbreaks, such as SARS and H1N1, were better prepared for the 2020 pandemic. Such firms therefore experienced higher equity returns than their peers. The authors develop text-based measures to capture firms' concerns regarding supply, demand as well as uncertainty about costs, benefits and risks associated with infectious diseases. Relatedly, Ramelli and Wagner (2020) analyse US firm characteristics that determine both stock market performance as well as discussions of Covid-19 in their earnings call transcripts early on in the pandemic. They find that internationally-oriented firms, especially those more exposed to trade with China, underperformed, and both corporate debt and cash holdings became important drivers of firm equity performance as the pandemic spread. In a similar vein, we rely on firms' quarterly earnings calls to measure their early exposure to the pandemic. However, we are more interested in investigating *heterogeneities* in Covid-19 related disclosures, and linking them to stock market performance not just at the time of the earnings calls, but also the first major set of pandemic-induced surprise policy announcements. We are less interested in linking these discussions to the extent of exposure these firms may have had to previous outbreaks like MERS and SARS, which were far less prevalent in India.

The announcements of Covid-19 induced lockdowns and mobility restrictions have been associated with significant negative stock market reactions (Ashraf, 2020; Scherf *et al.*, 2021). This is not surprising given their impact on economic activity. In our analysis therefore, we are interested in investigating whether specific sets of firms were worse affected than others, after controlling for the general impact on the broader stock market. For our case, if investors believed that firms discussing Covid-19 and its implications for their businesses early on in the year ("treated" firms) were also exposed to the virus, for example due to supply chains with China, then they are likely to make a downward revision in the expected future profitability, in response to the lockdown. Hence we would see that treated firms as a whole perform worse than their peers, i.e. the "control" firms.

On the other hand, if investors believed that early discussions of the pandemic implied that these "treated" firms were better prepared to weather the storm, then their returns would be better than their peers that seemed to have been caught off-guard. We hypothesise that the former is likelier than the latter, since it is not clear how firms could have unilaterally prepared for the shock (such as to demand disruptions) months in advance, especially given the uncertainty associated with the shock as well as with each country's policy response to it. This leads to our first hypothesis.

Hypothesis 1: The abnormal stock market returns of firms discussing the Covid-19 pandemic, the so-called "treated firms", *declined more* when the lockdown was announced, compared to their peers who did not discuss the pandemic as early as Jan-Feb, 2020.

There are several mechanisms or channels that might explain the differences in performance of Covid-mentioning versus non-mentioning firms at the time of the lockdown. For one, the mentioning firms might be more financially vulnerable. Indeed, since the onset of the pandemic, several studies have explored the role of financial flexibility in how firms to respond to big exogenous shocks and their subsequent performance (Fahlenbrach *et al.*, 2020), for example, based on their leverage and liquidity (Ding *et al.*, 2021; Ramelli and Wagner, 2020), ownership, supply chain structures, customer locations, and executive entrenchment (Ding *et al.*, 2021), environmental and social ratings (Albuquerque *et al.*, 2020) and corporate social responsibility (Ding *et al.*, 2021). Rahman *et al.* (2021) find that Australian stock markets responded significantly negatively to the declaration of Covid-19 as a public health emergency and then a pandemic. In their sample, size, profitability, and liquidity are key drivers of firms' stock market responses. Relatedly, papers have studied how firms perform conditional on their previous experience with rare disaster events (Hassan *et al.*, 2020), as well as exploited the informational content of past stock market reactions to pandemics for future events (Cakici and Zaremba, 2021). Accordingly, we draw on this literature to establish our hypothesis on the determinants of firm resiliency.

In the Indian context, Sane and Sharma (2020) calculated the liquidity cover of listed firms in the face of large revenue shocks during the pandemic, and concluded that more than a quarter of non-financial firms would be unable to handle a 30-day interruption of revenues. Bansal *et al.* (2020) also found that Indian firms which were more financially flexible, state-owned, had lower operational risks, had more concentrated ownership, and were affiliated with another firm, had higher market valuations in the early stages of the pandemic. We draw on this literature to shortlist possible confounding factors that might drive our results. Moreover, it may be the case that the mentioning firms belong to sectors that were more likely to be impacted – or differently impacted – by the lockdown (eg. hospitality *versus* health sectors; see, for example, Osotimehin and Popov (2020) for the US). We address these issues econometrically, by appropriately adjusting our fixed effects and including confounding variables directly into our cross-sectional regressions, similar to Hassan *et al.* (2020).

Hypothesis 2: The differences in the abnormal stock market returns between the treated and control firms can be explained by their pre-treatment differences in balance sheet characteristics.

To further explain these differences, we hypothesise regarding the *context* in which the pandemic is discussed. As the first country impacted by the spread of the disease, China introduced drastic measures early on in the pandemic, such as strict lockdowns and travel restrictions. It is possible that the treated firms were differentially linked to China, for example through their supply chain connections or reliance on Chinese markets. We would then expect that these firms' stock market returns would have fallen by more at the time of the Indian lockdown announcement - which necessarily cut off these firms' access to international markets and led to disruptions (see, for example, Meier and Pinto, 2020). To construct firm-specific measures of non-Covid-19 related exposure to China using earnings call reports, we apply a methodology similar to Hoberg and Moon (2017, 2018). Our third hypothesis is therefore:

Hypothesis 3: The differences in the abnormal stock market returns between the treated and control firms can be explained by differences in their linkages to China.

More generally, there may be supply chain linkages to other early-affected countries as well, which may be fundamentally different between our treated and control firms. There may also be differences in vulnerability to demand disruptions arising from the lockdown announcement that is distinct from the firm's sector but varies systematically across the two sets of firms. Hence we extend our textual analysis methodology to also count the number of references to supply and demand concerns in relation to the pandemic from the earnings call reports themselves, and hypothesise that:

Hypothesis 4: The differences in the abnormal stock market returns between the treated and control firms at the time of the lockdown announcement can be explained by differences in their international supply chain linkages and extent of concern around broader supply and demand disruptions.

Next, we measure the sentiment expressed by the firm's management in their discussion of the pandemic. If the sentiment expressed by managers of treated firms was particularly negative early on in 2020, then this might explain the lower abnormal returns witnessed by these firms at the time of the lockdown announcement. This would be in line with, for example, Price *et al.* (2012), who find that tone of the earnings call is a significant predictor of abnormal returns and trading volumes, and the question and answer part of the call is particularly informative. In the Indian context, the importance of business sentiments has been underlined by studies, such as Bhandari *et al.* (2021), whose findings based on a firm-level survey showcase a drastic worsening in firms' 6-months ahead sentiments for its financial conditions during the nation-wide lockdown. Thus, the impact of negative sentiments expressed during bad times, such as a pandemic is likely to be even more important (see, for example, García, 2013). Accordingly, as is commonly used in the literature, we measure the net sentiments expressed by each firm in its earnings call by taking the net sum of 'positive' and 'negative' words and scaling it by the total number of words in the report(Jiang *et al.* (2019); Loughran and McDonald (2011); Tetlock (2007)).

Hypothesis 5: The differences in the abnormal stock market returns between the treated and control firms at the time of the lockdown announcement can be explained by the negative managerial sentiments expressed by the former.

Finally, the systematic differences may also be explained by information *uncertainty* around pandemic-related discussions in the treated firms' earnings call reports. If these firms expressed uncertainty about how the onset of the pandemic might affect them, then investors may have taken a negative view on the firm, for example due to higher cash flow uncertainty, when the lockdown was announced. Uncertainty has a negative impact on most macroeconomic variables such as growth, as agents withhold investment due to its partial or complete irreversibility (see, for example, Bloom, 2009, among others). Relatedly, it has been shown in the literature that uncertainty leads to significant reductions in stock market returns and an increase in volatility (see, for example, Arouri *et al.*, 2016; Antonakakis *et al.*, 2013; Dzielinski, 2012).

Any discussion of uncertainty in a Covid-19 context by our treated firms would lead to an increase in ambiguity regarding the implications of this information for a firm's value. As discussed in Zhang (2006), greater information uncertainty about the impact of an event leads to lower expected stock returns following bad news, relative to stocks with lesser information uncertainty. Using the theoretical setup of Zhang (2006), let s be the overall observed signal of the fundamental value (v) of a firm - reflecting future cash flows or dividend payments - that discusses the pandemic in its earnings call reports, plus an additional noise component (e), such that

$$s = v + e. \tag{1}$$

The variance of the observed signal reflects information uncertainty, and is closely related to the idea that higher volatility makes it harder for agents to forecast the future (Bloom, 2014). Information uncertainty in this case can then be written as follows:

$$\sigma_s^2 = \sigma_v^2 + \sigma_e^2, \tag{2}$$

where σ_v^2 is the firm's underlying fundamental volatility and σ_e^2 is the quality of information disclosed. We expect that early discussions of uncertainty in a Covid-19 context would have increased both components, as the distribution of future firm fundamentals such as cash flows would have widened, and because the quality of information (for example on preparedness or expected impact) disclosed even before the pandemic assumed large proportions would have been poor or vague. As a result, information uncertainty would have increased. This would have resulted in lower stock market returns for early disclosing firms, compared to their peers.

Hypothesis 5: The differences in the abnormal stock market returns between the treated and control firms at the time of the lockdown announcement can be explained by admissions of pandemic-related uncertainty regarding the firm's future by the former.

The rapid spread of the Coronavirus was met with an equally swift response by policymakers to mitigate the economic damage and financial distress that was expected to follow. Swift actions by both monetary and fiscal authorities helped maintain easy global conditions and partially reversed some of the early stress (for a discussion of policy responses, see, for example, Cavallino *et al.* (2020) and Cantú *et al.* (2021) for advanced economies and Aguilar *et al.* (2020) for emerging economies). Heyden and Heyden (2021) study the short-term market reactions of US and European stocks at the beginning of the pandemic. They find that monetary policy measures have the capacity to calm markets, and that the reactions are either dampened or magnified based on firm characteristics.

Similarly, Ramelli and Wagner (2020) focus on the US Federal Reserve's March 23, 2020 intervention that announced facilities to support corporate credit provisioning, partially bolstered non-financial firms' stock market returns in the short term. Fahlenbrach *et al.* (2020) also study the same event, and find that more financial flexible firms benefitted less from the Fed's stimulus announcement. We contribute to this literature by studying the first major monetary policy announcement made against the background of the pandemic in a major emerging economy. To study its effectiveness on a large section of Indian non-financials, we exploit the fact that the central bank's policy package was a surprise to the markets.

Finally, we contribute methodologically by providing a way to extract and interpret early signals regarding a firm's exposures to tail risks, which can be expanded to other listed entities for a host of shocks and interesting events.

3 Data and descriptive analysis

3.1 Analysis of firms' earnings call reports

Earnings conference calls typically follow the presentation of a firm's quarterly results. These calls are hosted by the senior management of the firm (such as the chief executive officer or chief financial officer), who begin with short prepared remarks, and then open the floor to questions from market participants, investors, and financial analysts. Consequently, firms' earnings calls provide value-relevant information not only because of the disclosures of financial information, but also due to the interactive nature of the Q&A segment of the call which typically provides insights into analysts' and managers' opinions about the firm (Borochin *et al.*, 2018). For instance, managers are more likely to make forward-looking statements in earnings calls in response to analysts' questions (Frankel *et al.*, 1999), which is valuable information to participants, and one that we exploit here. For our purposes, the key advantage of these call transcripts as a source of information as compared to the firm's annual report – especially during crises – is that they are more spontaneous and timely. Lee (2015) finds that investors positively value managers' spontaneity in answering questions during earnings calls.

We start with a sample of the 500 largest firms listed in the Nifty 500 index of India's National Stock Exchange (NSE). Our main sample consists of the earnings calls transcripts from January-February 2020, of 196 firms, presenting their income results of October-December 2019. The first earnings call took place on 10 January 2020 and the last one on 26 February 2020. Of these, there are forty financial firms, which we exclude from our analysis from Section 4 onwards. For comparison purposes, we also extract earnings calls for 90 firms in April-May 2020. We obtain data on earnings call reports from Thomson Reuters Refinitiv.

We rely on the call reports of January-February 2020 to obtain signals of firms' exposure to the pandemic for two reasons. First, during this time the disease was still at a nascent stage in India (see Figure 1 for the case load), unlike in April-May 2020, when the impact of the pandemic, and the attendant policy actions, had spread to the entire economy. This can be seen, for instance, in the level of the internet search index for Covid-related keywords in Figure 1, which was quite low and stable through early-2020 and spiked only on the day of the lockdown announcement in March[3]. Second, there were no *direct* domestic policy interventions in the first two months of 2020. For instance, according to PRS Legislative Research, there were only 13 Covid-19 related notifications issued by the Indian government in February, most of them linked to international travel, as compared to 267 in March, 2020.[4] Hence, we expect that March onwards, all firms were likely to have become concerned about the risks associated with the pandemic, and also started adapting to government interventions, thereby making it a noisier period to study in comparison to the previous two months.

Moreover, we expect that at the time of the lockdown, investors would rely on the most recently available piece of information to guide their decisions, which underscores the relevance of the earnings calls reports of the January-February 2020. This behaviour would be in line with literature that finds that investors are susceptible to availability and recency biases.[5]

3.2 Measuring exposure and sentiment

We interpret any discussion of Covid-19-related words in a firm's call reports as an indicator of its *early exposure* to the pandemic. Accordingly, we check whether Covid-19 and related words are mentioned in the quarterly earnings call reports (see Appendix C for a full list of keywords). We consider a firm with at least one mention of Covid and related words, as treated and use a dummy variable to quantify exposure.[6] We do not differentiate between discussions initiated by either the analysts or the senior management, as both are informative. Managers can provide information that is directly relevant to the firm, while analysts have specific interest in the firm or the industry, and play a direct role in uncovering information during the discussion by asking questions (Matsumoto *et al.*, 2011).[7]

Word mentions, however, are agnostic to the context of the discussions. Therefore, we

[3] For more details on the computation of the keyword-based internet search index, refer to Priyaranjan and Pratap (2020)

[4] See `http://prsindia.org/covid-19/notifications`.

[5] See, for example, Nofsinger and Varma, 2013; Barber and Odean, 2008; Tversky and Kahneman, 1973, 1974, among others.

[6] One approach taken by the literature is to use the raw or scaled word counts, such as in Hoberg and Moon (2017); Buehlmaier and Whited (2018); Goel *et al.* (2021), among others. For our sample, the word counts range from 1 to 12, with a standard deviation of two, and therefore provide inadequate variation for exploitation. This is not unsurprising given that we are looking at earnings calls that took place before the pandemic was even declared so by the WHO (our last earnings call is on 26 February 2020, while the WHO declared the pandemic on 11 March 2020). Moreover, our approach of using a dummy rather than a continuous word count allows for potential non-linearities, i.e. the fact that an additional mention of the word is not likely to have the same impact on returns at each point in the distribution. Our implicit assumption is that the first mention is more informative than each additional discussion.

[7] In fact, Matsumoto *et al.* (2011) find that the discussion portion of the earnings call is relatively more informative to investors than the presentation part of the call.

undertake a few explorations to better understand the general *context* within which Covid-19 is discussed in each earnings call, as mentioned in detail in hypotheses 3-5 in Section 2. First, we measure the number of times China related words are mentioned in a non-Covid context in the earnings calls. This is intended to capture normal time or business-as-usual supply or demand dependence on China. Second, we extract the sentences where Covid-19 related words are mentioned. In these sentences, we look for mentions of "supply" and "demand", which are likely to be the most common channels of disruption that non-financial firms would be concerned about as a direct result of the pandemic and associated mobility restrictions. Third, to focus on discussions centered around pandemic-induced "uncertainty", we adopt the keywords from Sandile (2016) (see Appendix C).

Finally, it is also possible to have *positive* discussions around the pandemic, for example because of the *opportunities* it provided for expansion, diversification, or acquisition in certain sectors. Accordingly, we complement our keyword analysis with the construction of a *net sentiment* score for each firm-report. We adopt a lexicon-based methodology for sentiment computation as it is more transparent, efficient, and parsimonious compared to other popular techniques, such as through machine-learning algorithms. Calculation of the sentiment score rests on using two sentences before and after a Covid-19 related sentence in each report. For robustness, we vary the extracted sentences. We have provided the details of the sentiment score construction in Appendix E.

Descriptives

From Table 1, we find that only one-third of the firms in our January-February 2020 sample mention Covid-19 or related words (three of which are financial firms). By April-May 2020, all firms have at least one mention of Covid-19 or related words. The average occurrence of the words per report also increases by ten times, from three in the first two months of 2020, to close to 31 by April-May 2020. This reflects our earlier concern that from March onwards, all firms had become exposed to the pandemic, and hence, supports our choice to restrict the sample of earnings call transcripts to January-February 2020.

Out of the 60 firms that mention the pandemic at least once during their earnings call, 22 firms seem to be discussing supply-related issues while 6 firms discuss demand-related concerns in the context of the pandemic (and five who do both). All these are non-financial firms. The maximum number of supply-related mentions are found in the consumer goods sector (seven firms), followed by pharmaceuticals, industrial manufacturing, and automobiles. On the other hand there is no discernible pattern of interest in the demand mentions. The number of firms mentioning *uncertainty* in the context of the pandemic is larger by comparison. There are 33 firms (i.e. 55% of the total pandemic-mentioning firms) which have some reference to uncertainty regarding the future impact of Covid-19. The maximum number of firms with uncertainty-related mentions are in the consumer goods sectors (eight firms), followed by industrial manufacturing and pharmaceuticals, closely followed by services and automobiles sectors. Some examples of Covid-related sentences that mention uncertainty keywords are shows in Appendix D.

We see from Figure 2 that the treated and control firms are fairly similar in the overall unconditional sentiment expressed during the earnings call. There is no statistically significant difference in the average or median sentiment scores of these two groups, though, we see some possible differences between the two groups at the extreme ends of the distribution.

However, *conditional on mentioning Covid-19*, we observe that the treated firms overwhelmingly express negative sentiments. We see this in Figure 3, which depicts the box plots for net sentiment conditional on referring to the pandemic. Across all measures, both the mean (black cross) and median (black dash) are negative.

3.3 Firm balance sheet, stock market data, and summary statistics

We source firm balance sheet data, such as size, age, profits, foreign exchange earnings, inventories, and cash balances, for our sample of non-financial firms from the Prowess database provide by the Centre for Monitoring Indian Economy (CMIE). Using annual data allows for greater coverage of the firms in the sample, as quarterly data appears patchy. Stock market data, also taken from Prowess, is daily, as per availability. Additionally, restricting the balance sheet data to the financial year ending in March 2019, i.e. the pre-pandemic period, ensures that the firm characteristics are unaffected by the pandemic and reflect more "normal" conditions. Also, most of the firm financial variables are likely to be persistent and would reflect the conditions that these firms *enter* the pandemic with. This would make them relevant factors which must be controlled for when evaluating why certain firms may have under or overperformed during specific events of the pandemic.[8] In Table 2 we present detailed descriptive statistics and outline variable definitions.

We check whether there are any systematic differences between the set (out of the Nifty500) of non-financial firms for which we are able to get earnings call reports from Refinitiv, relative to those for which reports are not accessible. The concern would be that we have unknowingly selected a sample which is special for some reason, and not representative, for example due to higher reliance on foreign exchange earnings, which may drive our findings. In Table 3 we report the t-test of the differences in the main balance sheet characteristics across the included *versus* excluded firms. There are four variables which stand out. The included firms are on average younger, larger, have larger foreign exchange earnings and short-term borrowings. However, differences are not visible across most other balance sheet variables considered in our analysis. As a result, we include age and size in all our specifications. Moreover, most of these balance sheet variables are by themselves insignificant when included.

As shown in Table 4, we do not find any major difference in the characteristics of treated

[8]Additionally, Sane and Sharma (2020) look at the data for Indian non-financial firms between 2016 and 2019, and find that this is a period of relatively stable nominal values, i.e. low growth.

and control group of firms, except that the treated firms are on average older and hold higher tangible assets than the control group of firms. Similarly, Figure 5 shows that both group of firms witnessed a roughly 20% decline in their stock prices in the first twenty days of March 2020, reflecting the growing case load and number of pandemic-related policy announcements both domestically and internationally. The stock market performance of the two group of firms evolved in sync till about mid-March 2020, and diverged thereafter. The averages produced here nevertheless mask significant underlying heterogeneity, which we explore next.

4 Methodology and identification

In this section, we first discuss the extent to which the two events under consideration can be regarded as true surprises, in order to alleviate concerns around anticipation effects and confounding factors. We then outline our estimation strategy in detail.

4.1 "Surprise" events

While there is no direct way to measure whether the lockdown announcement was by itself a surprise, we rely on two key features of the policy's *intensity*. First, the policy came into effect pan-India with only a four-hour notice. Second, given the nature of restrictions covered by the policy, it was, at the time of announcement, by far the strictest lockdown of its kind anywhere in the world, as can be seen in panel (a) of Figure 1. As a result of these features, we do not expect any anticipation effects confounding our results.

To gauge the extent to which the RBI's policy package on 27 March 2020 was a surprise, we turn to a market measure of monetary policy surprises used in Mathur and Sengupta (2019). The monetary policy surprise on any given day is defined as the difference in 1-month overnight index swap (OIS) rate between the day before and the day of the central bank announcement. The surprise can be non-zero even on meeting days when the policy repo rate is not changed (for example, if market participants expect a change but it is not delivered). As we see from Figure 10, the 27 March 2020 meeting took market participants by surprise, and the extent of measures announced meant that they reacted positively.[9] In terms of the magnitude of the change in OIS rates, this meeting was the biggest surprise since the formal adoption of inflation targeting in India in October 2016.

4.2 Estimation strategy

In the first step of the estimation strategy, we run an event study model to obtain the cumulative abnormal stock market returns (CARs), for each firm over a window of $(-1, +1)$ days around the events of interest: the firm's earnings call, the lockdown

[9] The extent of the positive surprise can also be seen in leading English news commentary in India, for example, as reported by Business Standard, The Wire, Hindustan Times, and NDTV.

announcement of 24 March 2020 (Tuesday) and the RBI announcement of 27 March 2020 (Friday). To obtain these abnormal returns, we estimate a market model where we regress firm returns on movements in the $Nifty50$ index, which is the benchmark stock market index in India consisting of the 50 largest firms. This is intended to capture broader macroeconomic conditions, such as news on inflation and growth or the Covid-19 case load, among other factors, which could potentially impact firms' market performance. We estimate the market model, shown in equation 3, over a period of 81 days before the event, i.e. ($T-91$:$T-11$), where T is the event date. We depcit the event study process for the lockdown announcement in Figure 4. Specifically, we estimate,

$$R_{f,t} = \alpha + \beta \ R_{m,t} + \epsilon_t \tag{3}$$

where R is the daily return for firm f on day t. $R_{m,t}$ is the daily return on the $Nifty50$ index. Firm-wise abnormal returns (ARs) can then be calculated using $\widehat{R}_{f,T}$ estimated from equation 3 for each day in the event window as follows:

$$AR_{f,T} = R_{f,t} - \widehat{R}_{f,T}, \forall \ T = (-1, 0, +1) \tag{4}$$

In the next step, for ease of interpretation and comparison, we rebase the abnormal return on day (-1) in the event window equal to 0 and then cumulate the abnormal returns over the next days. For plotting purposes, we average the cumulative abnormal returns (CARs) for each day across all firms, and use bootstrapping to derive the 95% confidence intervals. These cumulative abnormal returns across firms are unconditional as they do not take into account differences across firm fundamentals like sector and balance sheet characteristics. The identification in our event study approach relies on stripping out the market conditions, and using a tightly defined window around the event date $(-1, +1)$. This reduces the likelihood that the results are driven by other confounding factors, whether macroeconomic or firm-specific (Gürkaynak and Wright, 2013). We then explore the determinants of the cumulative abnormal returns obtained above, using a cross-sectional regression model of the following form:

$$\begin{aligned} CAR_f = \alpha + \gamma_{sector} + \boldsymbol{\beta_1} \ COVID \ dummy \\ + \beta_2 \ log(age)_f + \beta_3 \ log(size)_f + \beta_4 \ X_f + \epsilon_f \end{aligned} \tag{5}$$

where γ_{sector} are sector dummies, and X_f is a set of firm f specific financial variables. Among the regressors, of particular interest is the COVID dummy which takes a value one for the treated group of firms. It should be interpreted as the difference in post-event CARs between the treated and the control firms. A negative value for β_1 would imply that the treated group has a *lower* CAR around the event, which would support our hypothesis 1 outlined in Section 2. Sector fixed effects ensure that we compare firms within the same sector, as the impact of the lockdown was likely to be heterogenous across different sectors.

The firm specific financial variables included sequentially in equation 5 are shown in Table 4. Based on the existing literature, as discussed in Section 2, we focus on variables such as profitability, foreign exchange earnings, operating expenses, inventories, trade receivables, and cash holdings. These variables reflect underlying fundamental characteristics that could drive the responses of a firm's stock market return to the event under consideration.

An important identifying assumption is that the treated and the control firms are not fundamentally different and the only aspect that sets them apart is that the former group of firms disclosed their early exposure to the pandemic (as measured by our text-based metric) compared to the latter group. To establish this we have already shown in Table 4 that there are no major differences in the characteristics of these two groups of firms, except age and inventories. Including these variables in our regression specifications is another way of taking care of the identification. Age and size stand out in terms of variables that are significantly different either between treated and control firms in our sample, or between the Nifty500 firms for which we have access to earnings call reports and for which we do not (Table 3). Therefore, we always control for age and size in all our specifications.

To test our alternative hypotheses, we include additional explanatory variables as shown in equation 6.

$$\begin{aligned} CAR_f = \alpha + \gamma_{sector} + \boldsymbol{\beta_1}\ COVID\ dummy + \boldsymbol{\beta_{1A}}\ Alt.\ explanation \\ + \beta_2\ log(age)_f + \beta_3\ log(size)_f + \beta_4\ X_f + \epsilon_f \end{aligned} \tag{6}$$

Here, the vector of alternative explanations includes sequentially, a dummy for whether a firm mentions China in a non-Covid context, a dummy for whether the firm mentions either supply or demand in a Covid context, the sentiment expressed around the Covid discussion, and a dummy for whether the firm mentions uncertainty in a Covid context.

5 Results and discussion

Raw event study results

First, to establish that earnings calls are viewed as crucial vehicle of voluntary value-relevant information disclosures, we investigate whether the treated and control firms' stock market returns were significantly different around their earnings calls (which occurred between 10 January and 26 February 2020). In Figure 6 we show the raw average

CARs estimated using equation 3, around each firm's own earnings call date.[10] We see that while the control group of firms witness almost no change in their CARs, there is about a 0.4% *reduction* in the CARs of the treated firms on the day after their earnings call.

In Figure 7 we depict the raw CARs for the first lockdown on 24 March 2020. We find that while both treated and control group of firms faced declines in their stock market returns at the end of the event window on 25 March 2020, the decline was *greater* for treated firms.

The raw CARs for the RBI announcement on 27 March 2020 can be seen in Figure 8. Since the announcement was on a Friday, the end of our event window is on 30 March 2020, i.e. the following Monday. We do not expect this to create any issues with our estimates; in fact, as the market would have had the intervening weekend to process the policy package, the timing makes it *less likely* that we would find any significant differences between the two groups of firms by the close of markets and end of our event window on Monday. Despite this limitation, we find that while both groups of firms reacted positively after the RBI announcement, treated firms performed *better* than control firms.

Differences between treated and control firms, and heterogeneities

The event study results that we presented above are unconditional, and differences across firms could potentially be explained away if the treated and control firms belong to specific sectors that were expected to be more or less affected by the pandemic and associated lockdowns. Therefore, in the next step, we undertake a cross-sectional regression analysis by including sectoral fixed effects, so that the resulting estimates are based on comparisons with firms within the same sector.

We present the baseline results in Tables 5 and 6. Comparing column (1) of Table 5 to the remaining columns we find that the differences between the two groups become stronger – both statistically and economically – after controlling for sector fixed effects. We control for age and size of the firm in each columns and include the balance sheet variables sequentially. We find that the stock returns of treated firms, i.e. those that mentioned Covid-19 in their call reports early on in 2020, significantly and consistently underperform compared to the control firms at the 90% confidence level or more, across all specifications. Column (2) indicates that the CARs of control firms were 11.37% lower around the lockdown announcement (constant), while those of treated firms were lower by 14.3%, indicating a difference of 2.9 percentage points (coefficient on the COVID dummy). Overall, returns of the treated firms are roughly 3 to 5 percentage points lower across specifications.

Most of the included financial variables have the expected signs. For instance, the stock

[10]For this analysis, the market model is calculated for 91 days before each firm's individual earnings call date, after which we convert the call date into event time to obtain the CARs. The remaining procedure is the same.

returns of more profitable firms outperformed by about 8 percentage points compared to those of less profitable ones. Firms with higher pre-pandemic trade credit reliance and operating expenses saw significantly lower abnormal returns, by between 11 to 16 percentage points. These are in line with the argument that lower profitability, higher trade credit reliance, and higher operating expenses all indicate a lack of financial flexibility of firms in the face of unexpected shocks such as the pandemic-induced lockdown announcement.

Discussion of mechanisms

Having established this difference in the behaviour of CARs for treated and control firms at the time of the lockdown announcement, we next try to *explain* the potential mechanisms that might explain these differences. We start by investigating whether the two sets of firms differ in their non-pandemic related mentions of China. A simple t-test indicates that the treated firms do have significantly higher mentions of China in non-pandemic related sentences - this may indicate greater connections to the country, either through demand or supply-chain linkages

As suggestive evidence, we first investigate whether the cumulative abnormal returns of the treated firms were significantly different from the control firms on 23 January, 2020 when the first lockdown was announced in the Chinese city of Wuhan. If investors believed that this first lockdown was an early sign of the spread of the coronavirus and the potential measures that the Chinese government was willing to take, then we would expect to see this concern translated into negative abnormal returns for our treated Indian firms if indeed they had more supply or demand connections with that country. However, we can see in Figure 9, the unconditional CARs of the two groups of firms were in fact positive. Cross-sectional regressions with sector fixed effects and other balance sheet characteristics confirm that these differences are not significant at any conventional levels.[11] This exercise indicates that investors did not differentiate between our treated and control group of firms based on their pre-existing connections to China at the onset of the outbreak in Wuhan. We consequently expect similar results at the time of the Indian lockdown announcement.

To explore the linkages between connections to China and abnormal returns during the Indian lockdown announcement, we include a dummy variable to capture whether the firm mentions China in a non-pandemic context. We show this in Table 7. Accounting for this fundamental difference between the firms would ensure that any statistical and economic significance of the coefficient of interest, the COVID dummy, would be free of confounding factors. As we see in Table 7, our main result does not change. The COVID dummy continues to be negative and statistically significant across all sequential additions of firm-specific financial variables even when we include this additional control. The dummy on non-pandemic China mentions is by itself statistically insignificant, indicating

[11] These regressions are similar in setup to those in Table 5, but are not reported here for brevity. They are available on request.

that fundamental connections to the Chinese economy across the treated and control firms are potentially being picked up by differences in the sectors, balance sheet characterisitics, and business models of firms.

Another potential explanation for the differences in CARs of treated and control firms might be related to general supply and demand disruptions caused by the lockdown. If the treated firms had already discussed these channels as potential issues when discussing the pandemic in their earnings calls as early as January-February 2020, then investors may have taken a particularly negative view of their future cash flows at the time of the lockdown announcement in March 2020 when these risks materialised. We include dummy variables to capture whether a firm mentions supply or demand, in the pandemic context, separately as additional controls in Table 8. Note that a firm can only mention supply or demand in a Covid-context if it has non-zero discussions of the pandemic in the first place. Therefore, the coefficient on these variables indicates the difference between the CARs of supply (or demand) mentioning firms relative to those who discuss Covid but do not mention these additional keywords, as well as the non-Covid mentioning control firms.

Column 8 in particular accounts for different levels of internationalisation of firms through their foreign exchange earnings, as well as profitability of firms, their cash holdings, non-pandemic or business-as-usual China-connections, pre-existing inventories, operating expenses and reliance on trade credit. In general, the coefficient on our main variable of interest, i.e. whether the firm mentions Covid-19 in its earnings call reports, stays negative and highly statistically significant, with higher economic magnitudes (roughly 4.8 percentage points in column 8).

The results may also be driven by those Covid-discussing firms which express particularly negative sentiments. As discussed earlier, our main measure of sentiment is constructed using two sentences before and after a Covid-mentioning sentence. This variable is therefore only defined for the treated firms. The coefficient on this variable is indicative of the evolution of CARs of the treated firms that expressed a unit more negative sentiment in their earnings calls, relative to the control firms. We show the results in Table 9. The coefficients on the sentiment variable are negative but statistically insignificant. This is unsurprising given that, as mentioned earlier, conditional on mentioning Covid, most firms express a negative sentiment (recall Figure 3). Interpreting only the sign, the coefficient reflects an intuitive result: firms which expressed greater concern about the impact of the pandemic (rather than discussing its opportunities), experienced worse cumulative abnormal returns at the time these risks materialised.

Including this additional variable does not explain away the differences between treated and control firms. We see in column 8 of Table 9 that the differences in CARs of the two groups continues to be significant both statistically and economically, even after we control for a host of balance sheet characteristics. This result also holds when we use apply alternative methodologies to construct sentiment scores, such as using valence-shifting clusters with two sentences before and after Covid-mentioning sentences in Table 12 and using valence-shifting bigrams with five sentences before and after Covid-mentioning sentences in Table 13.

Finally, we turn to our last hypothesis. We posit that the differences in returns across treated and control firms arise due to an an acknowledgement in the earnings calls that the impact of the pandemic on the firm was likely to be *uncertain*. As we discuss in Section 2, this would have reflected an increased ambiguity in how the new information affects the firm's value. In that situation, the lockdown announcement would have been a further shock to the dispersion of (an already widened) future cash flow distribution, leading to more negative stock market returns.

We include a dummy variable to capture whether the firm mentions uncertainty in a Covid-context. As with the variables above, it is an implicit interaction variable which tells us the difference in the CARs of a treated firm *which also mentions uncertainty*, relative to its peers who mention the pandemic but not uncertainty related to it, as well as the controls firms that do not mention Covid. In Table 10, we can see that the inclusion of this variable explains away our main results. The coefficient on the Covid mentions dummy is now smaller in magnitude and statistically insignificant in most of the specifications. In turn, the uncertainty dummy is statistically significant at 10% levels in several of the specifications, indicating that the results were being driven by Covid-mentioning firms who were themselves uncertain regarding how the pandemic would impact them.

In summary, we find that there exist significant differences in the stock market performance of firms who discussed the pandemic early on relative to those who did not, when the lockdown was announced. Accounting for fundamental differences across these groups of firms, such as their sectors, balance sheets, linkages to China, or concerns around supply and demand disruptions does not explain these differences. We find strong evidence in support of the information uncertainty hypothesis.

6 Impact of central bank's policy announcement

In this section, we investigate the impact of the unexpected policy announcement by the Reserve Bank of India on the treated firms. On March 27, 2020 the RBI made an unscheduled monetary policy announcement wherein it implemented several conventional and unconventional policy actions in the face of the pandemic (Talwar *et al.*, 2021). Conventional policy announcements consisted of a decrease of 75 basis points (bps) in the policy repo rate and 100 bps reduction in cash reserve ratio (CRR) for banks. Unconventional policy announcements included (i) liquidity support to the corporate sector through targeted long term repo operations conducted with the banks; (ii) moratorium on loan payments for the following three months to provide relief to all categories of borrowers including non-financial firms; and (iii) easing of working capital financing. As a result of its unscheduled nature, this announcements was considered the biggest surprise by the markets since India adopted Inflation Targeting (recall Figure 10 and the discussion in

4.1).

We expect that the extent of policy easing encapsulated in this announcement would have benefitted the treated firms by more, and in particular, those treated firms which were uncertain about the future impact of the pandemic. This is because the announcement of supportive measures by the central bank would have mitigated the adverse impact of the lockdown – or at least countered it to some extent – and therefore provided some relief for the affected firms. Using the framework described in Section 2, the policy easing would have reduced the treated firms' fundamental (eg. cash flow) volatility, as well as provided greater clarity on how the pandemic would affect the firm. In this way, it would increase the relative stock market returns of the treated firms.

We conduct the same cross-sectional regression analysis as outlined in equation 5 in order to estimate the impact of the RBI announcement on the treated firms. As before, we control for the sector, firm age, size as well as a host of other firm-specific financial variables that may potentially explain the response of firms to the RBI's announcement.

We present the estimation results in Table 11. We find that the event of March 27 had a positive as well as statistically significant effect on the treated firms who significantly outperformed (at the 90% confidence level or higher) compared to the control firms. The returns of treated firms were roughly 2.4 percentage points higher, as can be seen in column 1 of Table 11. The result is robust to controlling for firm-specific characteristics as well as sector dummies. However, as before, including the uncertainty variable in column 3 explains away these differences, even if the variable is statistically insignificant itself.

Therefore it seems that while the lockdown announcement of March 24 resulted in negative abnormal returns for the treated non-financial firms in our sample, the RBI's policy announcement of March 27 had the opposite effect, leading to positive abnormal returns between the day of the event and the next trading day. The economic magnitude of the impact also hints at the possibility that the unexpected policy announcement by the RBI may have helped overturn the negative impact of the lockdown announcement for our sample of treated firms, at least in the short term. These results therefore provide evidence in support of the RBI's policy package, both its timing as well as its content.

7 Conclusion

Using the informational content of earnings call reports of a set of large non-financial firms in India, we throw light on the firms that may have been exposed to the pandemic as early as January and February 2020, when as per the official statistics, the disease had still not spread in India. We find that these firms fared worse in terms of stock market returns when a nationwide lockdown was announced in India on March 24, 2020 compared to firms that were presumably less exposed to the pandemic early on.

Our result is robust to accounting for pre-existing financial vulnerabilities of the firms, exposure to China, discussions regarding supply linkages or demand concerns and also negative sentiment expressed in context of the pandemic in the firms' call reports. We find strong evidence that Covid-mentioning firms that expressed greater uncertainty regarding the impact of the pandemic in their earnings calls were worse affected when the lockdown was announced. The Reserve Bank of India's surprise monetary policy announcement on March 27, 2020 seemed to have reversed the initial adverse impact of the lockdown announcement especially for firms that had early exposure to the pandemic.

The findings of our study have important policy implications. By creating a measure of firms' exposure to the pandemic, we throw light on the kind of firms that were more adversely impacted by a stringent lockdown announcement. We also provide a method to extract and interpret early signals regarding a firm's exposure to tail risks, which can be expanded to other listed entities for a host of shocks and interesting events. We further highlight the role policy actions can play in mitigating the negative impact of an economy-wide shock on firms and providing them with much-needed breathing space.

In future work we plan to track the performance of our sample of exposed firms throughout the duration of the pandemic, and compare and contrast this with the performance of their peers who did not discuss the pandemic early on in 2020. We aim to analyse the impact of future policy announcements in context of the pandemic on these two sets of firms. More generally, we plan to use measures of business sentiment as expressed by the firms in their earnings call reports to construct forward-looking indicators of firm health and performance.

References

Aguilar A, Cantú C, *et al.* (2020). "Monetary policy response in emerging market economies: why was it different this time?" *Technical report*, Bank for International Settlements.

Albuquerque R, Koskinen Y, Yang S, Zhang C (2020). "Resiliency of environmental and social stocks: An analysis of the exogenous Covid-19 market crash." *The Review of Corporate Finance Studies*, **9**, 593–621.

Algaba A, Ardia D, Bluteau K, Borms S, Boudt K (2020). "Econometrics meets sentiment: An overview of methodology and applications." *Journal of Economic Surveys*, **34**(3), 512–547.

Antonakakis N, Chatziantoniou I, Filis G (2013). "Dynamic co-movements of stock market returns, implied volatility, and policy uncertainty." *Economics Letters*, **120**, 87–92.

Arouri M, Estay C, Rault C, Roubaud D (2016). "Economic policy uncertainty and stock markets: Long-run evidence from the US." *Finance Research Letters*, **18**, 136–141.

Ashraf BN (2020). "Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets." *Journal of Behavioral and Experimental Finance*, **27**, 100371.

Bansal A, B G, Jacob J, , Srivastava P (2020). "When the market went viral: COVID-19, stock returns, and firm characteristics." Available at SSRN (21 Jun, 2020).

Barber BM, Odean T (2008). "All that glitters: The effect of attention and news on the buying behaviour of individual and institutional investors." *Review of Financial Studies*, **21**, 785–818.

Bhandari B, Gupta S, Sahu AK, Urs K (2021). "Business sentiments during India's national lockdown: Lessons for second and potential third wave." *Indian economic review*, pp. 1–16.

Bloom N (2009). "The impact of uncertainty shocks." *Econometrica*, **77**, 623–685.

Bloom N (2014). "Fluctuations in uncertainty." *Journal of Economic Perspectives*, **28**, 153–176.

Borochin PA, Cicon JE, DeLisle J, Price SM (2018). "The effects of conference call tones on market perceptions of value uncertainty." *Journal of Financial Markets*, **40**(C), 75–91.

Buehlmaier M, Whited T (2018). "Are financial constraints priced? Evidence from textual analysis." *Review of Financial Studies*, **31**(7), 2693–2728.

Bushee BJ, Matsumoto DA, Miller GS (2003). "Open versus closed conference calls: the determinants and effects of broadening access to disclosure." *Journal of Accounting and Economics*, **34**(1-3), 149–180.

Bushee BJ, Matsumoto DA, Miller GS (2004). "Managerial and investor responses to disclosure regulation: The case of Reg FD and conference calls." *The Accounting Review*, **79**(3), 617–643.

Cakici N, Zaremba A (2021). "Who should be afraid of infections? Pandemic exposure and the cross-section of stock returns." *Journal of International Financial Markets, Institutions and Money*, **72**(C), 101333–101357.

Cantú C, Cavallino P, De Fiore F, Yetman J, *et al.* (2021). *A global database on central banks' monetary responses to Covid-19*. Bank for International Settlements, Monetary and Economic Department.

Castelnuovo E, Tran TD (2017). "Google it up! A google trends-based uncertainty index for the United States and Australia." *Economics Letters*, **161**, 149–153.

Cavallino P, De Fiore F, *et al.* (2020). "Central banks' response to Covid-19 in advanced economies." *BIS Bulletin*, **21**(June).

Ding W, Levine R, Lin C, Xie W (2021). "Corporate immunity to the COVID-19 pandemic." *Journal of Financial Economics*, **141**, 802–830.

Dzielinski M (2012). "Measuring economic uncertainty and its impact on the stock market." *Financial Research Letters*, **9**, 167–175.

Fahlenbrach R, Rageth K, Stulz RM (2020). "How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis." *NBER Working Papers 27106*, National Bureau of Economic Research.

Fama E (1990). "Stock returns, expected returns, and real activity." *Journal of Finance*, **45**(4), 1089–1108.

Frankel R, Johnson M, Skinner DJ (1999). "An empirical examination of conference calls as a voluntary disclosure medium." *Journal of Accounting Research*, **37**(1), 133–150.

García D (2013). "Sentiment during Recessions." *Journal of Finance*, **68**(3), 1267–1300.

Goel T, Lewrick U, Mathur A (2021). "Does regulation only bite the less profitable? Evidence from the too-big-to-fail reforms." *Staff Working Paper 946*, Bank of England.

Goldstein I, Koijen RSJ, Mueller HM (2021). "Covid-19 and its impact on financial markets and the real economy." *Review of Financial Studies*, **34**.

Gürkaynak R, Wright JH (2013). "Identification and inference using event studies." *Manchester School*, **81**, 48–65.

Hassan TA, Hollander S, van Lent L, Tahoun A (2020). "Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1." *NBER Working Papers 26971*, National Bureau of Economic Research.

Heyden KJ, Heyden T (2021). "Market reactions to the arrival and containment of Covid-19: An event study." *Finance Research Letters*, **38**, 101745.

Hoberg G, Moon SK (2017). "Offshore activities and financial vs operational hedging." *Journal of Financial Economics*, **125**(2), 217–244.

Hoberg G, Moon SK (2018). "The offshoring return premium." *Management Science*, **65**(6), 2876–2899.

International Monetary Fund (2021). "Fiscal monitor: A fair shot." *Technical report*.

Jiang F, Lee J, Martin X, Zhou G (2019). "Manager sentiment and stock returns." *Journal of Financial Economics*, **132**, 126–149.

Kamber G, Mohanty MS (2018). "Do interest rates play a major role in monetary policy transmission in China?" *BIS Working Papers No. 714*, Bank for International Settlements.

Lee J (2015). "Can investors detect managers' lack of spontaneity? Adherence to predetermined scripts during earnings conference calls." *The Accounting Review*, **91**(1), 229–250.

Lopatta K, Ernst-Kenji A, Gastone L, Tammen T (2020). "To report or not to report about coronavirus? The role of periodic reporting in explaining capital market reactions during the global Covid-19 pandemic." *Technical report*, Available at SSRN.

Loughran T, McDonald B (2011). "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance*, **66**(1), 35–65.

Loughran T, McDonald B (2020). "Management disclosure of risk factors and Covid-19." *Technical report*, Available at SSRN.

Mathur A, Sengupta R (2019). "Analysing monetary policy statements of the Reserve Bank of India." *IHEID Working Papers 08-2019*, Economics Section, The Graduate Institute of International Studies.

Matsumoto D, Pronk M, Roelofsen E (2011). "What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions." *The Accounting Review*, **86**(4), 1383–1414.

Meier M, Pinto E (2020). "Covid-19 supply chain disruptions." *Covid Economics*, **48**.

Nofsinger JR, Varma A (2013). "Availability, recency, and sophistication in the repurchasing behavior of retail investors." *Journal of Banking and Finance*, **37**, 2572–2585.

Osotimehin S, Popov L (2020). "Sectoral Impact of COVID-19: Cascading Risks." *Opportunity and Inclusive Growth Institute Working Papers 31*, Federal Reserve Bank of Minneapolis.

Price MS, Doran JS, Peterson DR, Bliss BA (2012). "Earnings conference calls and stock returns: The incremental informativeness of textual tone." *Journal of Banking and Finance*, **36**, 992–1011.

Priyaranjan N, Pratap B (2020). "Macroeconomic effects of uncertainty: a big data analysis for India." *RBI Working Paper Series, Reserve Bank of India*, (04).

Rahman LM, Amin A, Al Mamun MA (2021). "The Covid-19 outbreak and stock market reactions: Evidence from Australia." *Finance Research Letters*, **38**, 101832.

Ramelli S, Wagner AF (2020). "Feverish stock price reactions to COVID-19." *The Review of Corporate Finance Studies*, **9**(3), 622–655.

Sandile H (2016). "Unpacking policy uncertainty: Evidence from European firms." *Unpublished manuscript*, URL https://bit.ly/2XL8gpQ.

Sane R, Sharma A (2020). "Holding their breath: Indian firms in an interruption of revenue." The Leap Blog (03 Apr, 2020). URL https://blog.theleapjournal.org/2020/04/holding-their-breath-indian-firms-in.html.

Scherf M, Matschke X, Rieger MO (2021). "Stock market reactions to Covid-19 lockdown:A global analysis." *Forthcoming*.

Sever C, Goel R, Drakopoulos D, Papageorgiou E (2020). "Effects of emerging market asset purchase program announcements on financial markets during the Covid-19 pandemic." *Working paper WP/20/292*, International Monetary Fund.

Talwar BA, Kushwaha KM, Bhattacharya I (2021). "Unconventional Monetary Policy in Times of COVID-19." *RBI Bulletin*, **75**(March).

Tetlock PC (2007). "Giving content to investor sentiment: The role of media in the stock market." *Journal of Finance*, **62**, 1139–1168.

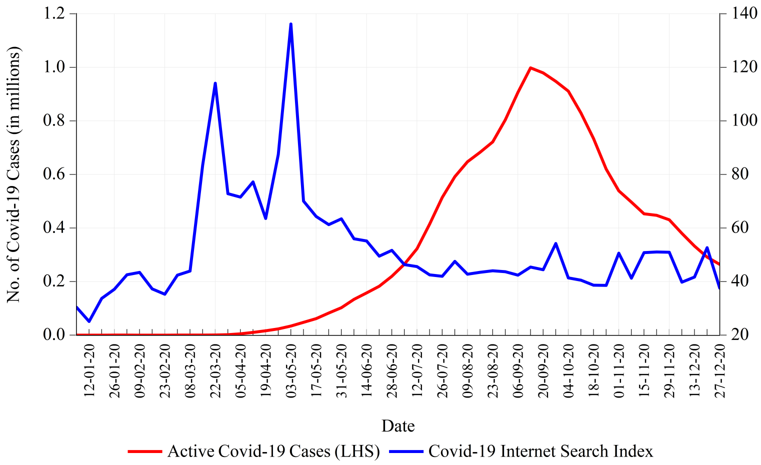
Tversky A, Kahneman D (1973). "Availability: A heuristic for judging frequency and probability." *Cognitive Psychology*, **5**, 207–232.

Tversky A, Kahneman D (1974). "Judgement under uncertainty: Heuristics and biases." *Science*, **185**, 1124–1131.

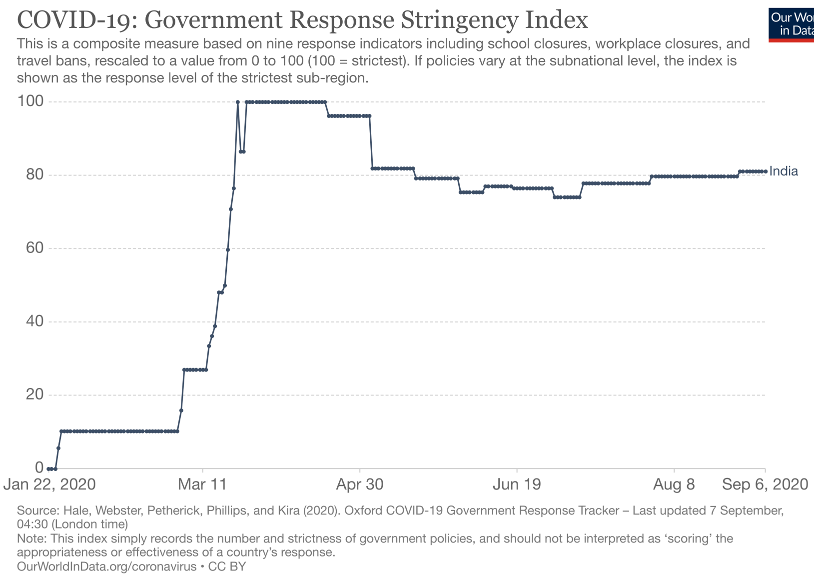
Zhang XF (2006). "Information Uncertainty and Stock Returns." *Journal of Finance*, **61**(1), 105–137.

Tables and Figures

Figure 1 Covid-19 cases, web searches and lockdown stringency in India



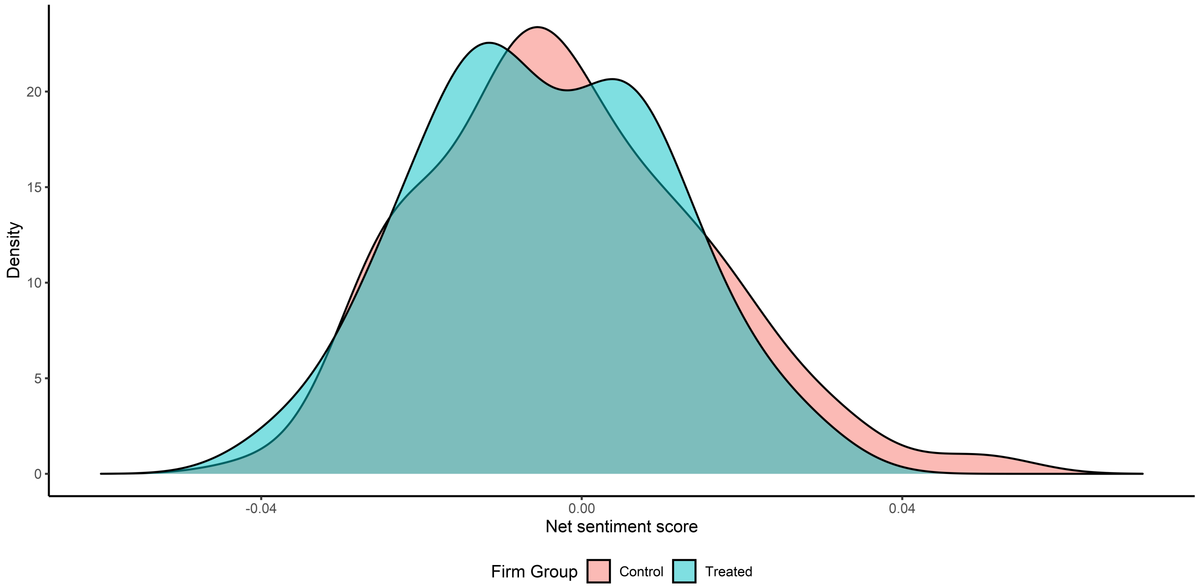
(a) Covid-19 caseload and web search index



(b) Oxford Covid-19 government response stringency index

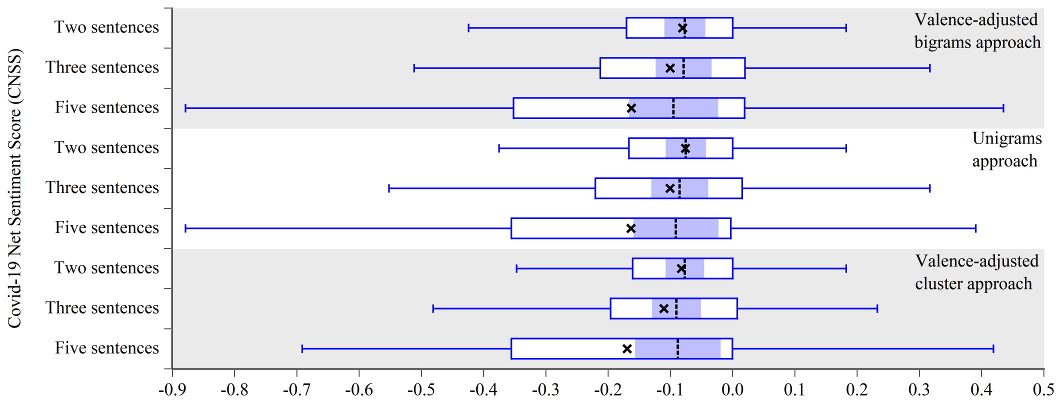
Note: The *top panel* shows the total number of active COVID-19 cases in India (solid red line) and the internet search intensity index (solid blue line) for pandemic-related search terms. The internet search intensity index was constructed based on the algorithm discussed in Castelnuovo and Tran (2017) and Priyaranjan and Pratap (2020). The *bottom panel* shows the government response stringency index for India compiled by the Oxford COVID-19 Government Response Tracker, Blavatnik School of Government, University of Oxford.

Figure 2 Valence-adjusted overall net sentiment score for firms



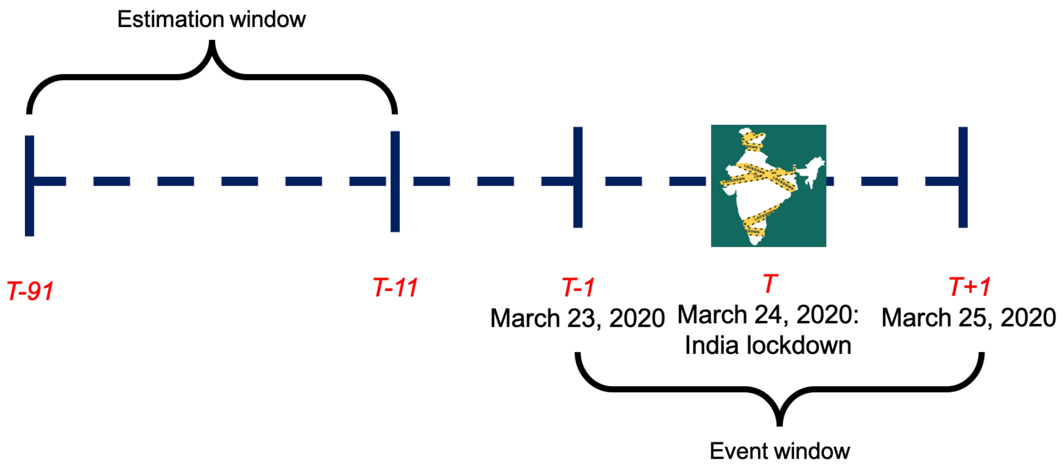
Note: The figure shows the probability density function of the valence-adjusted net sentiment score for the control and treated group of firms. The probability density function was estimated using the kernel density estimation method.

Figure 3 Net sentiment around Covid-19 pandemic



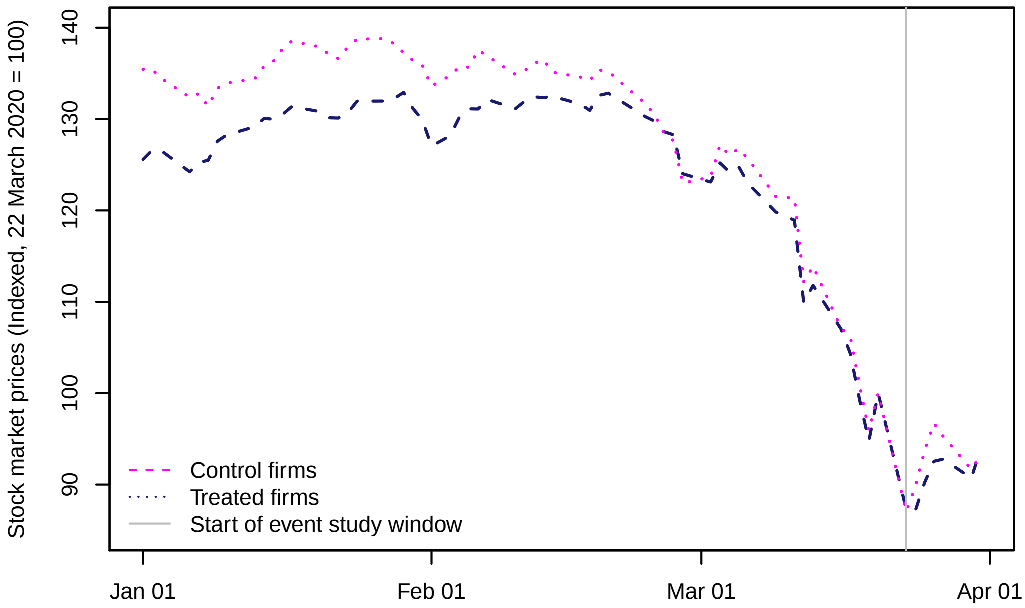
Note: The figure shows the boxplots for COVID-19 net sentiment score (CNSS) computed using alternative sentiment computation approaches *viz.,* the simple unigram approach, the valence-adjusted bigrams approach and the valence-adjusted clusters approach with two, three and five sentences before and after pandemic-related keyword terms in the earnings call reports of treated firms. The solid black cross shows the mean whereas the dashed black line depicts the median value for the respective CNSS distribution.

Figure 4 Event study estimation strategy for the lockdown announcement



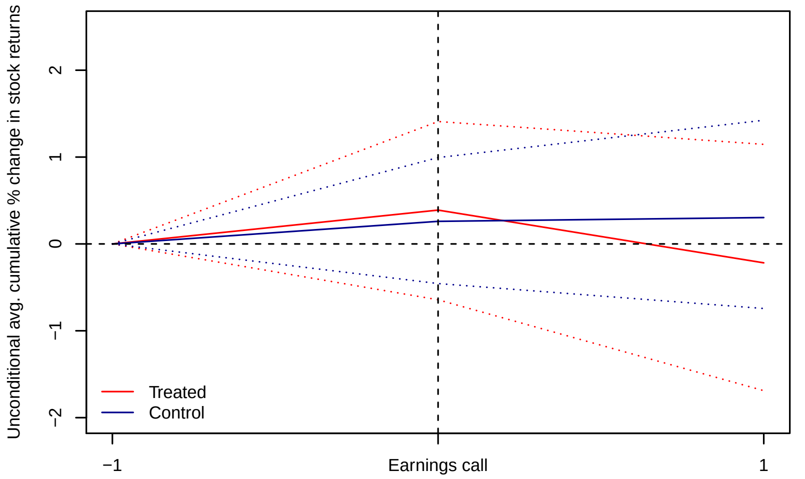
Note: The figure shows the event study estimation strategy. The market model of equation 3 is first estimated using data from 91 days before to 11 days before the event T. As shown in equation 4, the estimates for the $\hat{alpha}$ and $\hat{beta}$ are then used to calculate the cumulative abnormal returns in the window of one day before to one day after the event under study. This example shows the lockdown announcement, but we also study the RBI policy announcement on 27 March 2020 and also each firms' earnings call dates.

Figure 5 Stock market performance of treated and control firms



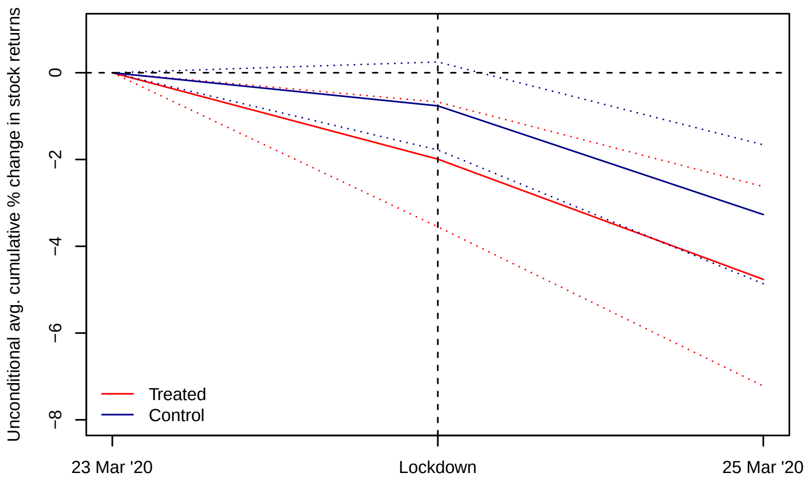
Note: The graph shows the stock market performance of treated and control firms from 01 January 2020 to 31 March 2020. Prices are first averaged across each group, and then indexed to 22 March 2020, the day before the beginning of our analysis period (which in turn is indicated by the grey vertical line).

Figure 6 Event study: Earnings call dates



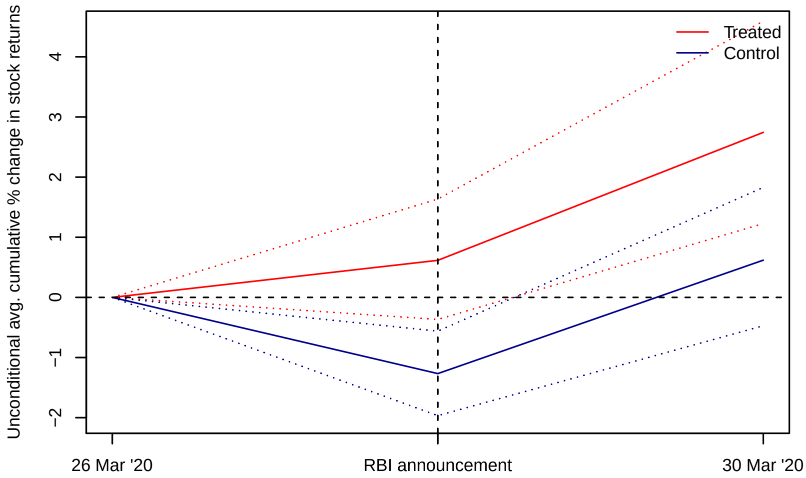
Note: The figure shows the cumulative abnormal returns, based on equations 3 and 4 and figure 4, around the earnings call dates of Indian non-financials. "Treated" non-financial firms (N = 58) are those who discuss Covid-19 in their earnings call reports from January-February 2020, and "control" firms (N = 93) are those who do not mention Covid-19 over the same time period. We use an estimation window of (-91,-11) days before each event and an event window of (-1, +1) around the event date. The results are qualitatively similar to using alternate event windows.

Figure 7 Event study: Lockdown announcement of 24 March, 2020



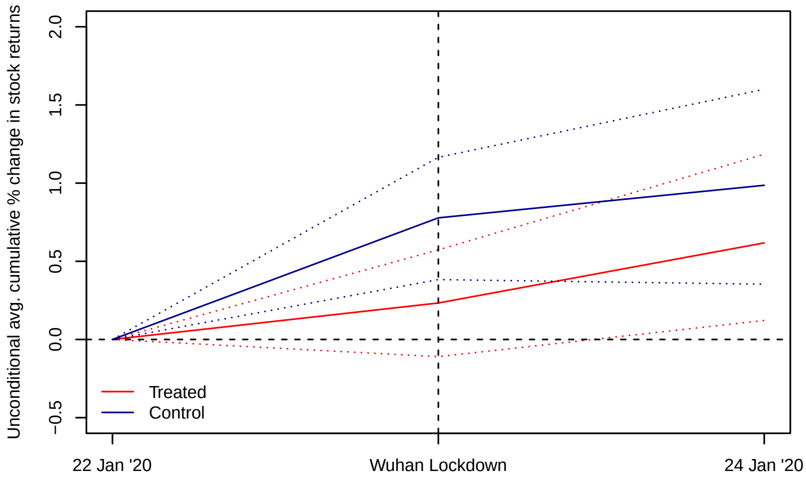
Note: The figure shows the cumulative abnormal returns, based on equations 3 and 4 and figure 4, for the first lockdown on 24 March 2020. "Treated" non-financial firms (N = 58) are those who discuss Covid-19 in their earnings call reports from January-February 2020, and "control" firms (N = 93) are those who do not mention Covid-19 over the same time period. We use an estimation window of (-91,-11) days before each event and an event window of (-1, +1) around the event date. The results are qualitatively similar to using alternate event windows.

Figure 8 Event study: RBI announcement of 27 March, 2020



Note: The figure shows the cumulative abnormal returns, based on equations 3 and 4, for the surprise RBI announcement on 27 March 2020. Since the announcement was on a Friday, the "+1" refers to 30 March 2020, i.e. the following Monday. "Treated" non-financial firms (N = 58) are those who discuss Covid-19 in their earnings call reports from January-February 2020, and "control" firms (N = 93) are those who do not mention Covid-19 over the same time period. We use an estimation window of (-91,-11) days before each event and an event window of (-1, +1) around the event date. The results are qualitatively similar to using alternate event windows.

Figure 9 Event study: Lockdown announcement in Wuhan, China on 23 January, 2020



Note: The figure shows the cumulative abnormal returns, based on equations 3 and 4 and figure 4, for the first lockdown in Wuhan, China on 23 January 2020. "Treated" non-financial firms (N = 58) are those who discuss Covid-19 in their earnings call reports from January-February 2020, and "control" firms (N = 93) are those who do not mention Covid-19 over the same time period. We use an estimation window of (-91,-11) days before each event and an event window of (-1, +1) around the event date. The results are qualitatively similar to using alternate event windows.

Table 1 Overall mentions of Covid19 in Q3 and Q4 FY20

	Quarter	Total mentions	No. of reports	Avg. words per report
1	January-February 2020	189	63 ($N = 196$)	3
2	April-May 2020	2,781	90 ($N = 90$)	30.900

Note: This table presents the total (column 2) and average (column 4) number of Covid19-related mentions in the sample of earnings call reports. There are 196 reports for January-February 2020 and 90 reports for April-May 2020, from the initial sample of Nifty 500.

Table 2 Summary statistics: Sample of non-financial firms

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel A: Text-based variables							
COVID word count (raw)	156	1.224	2.285	0	0	2	12
COVID word count (scaled, %)	156	0.009	0.017	0.000	0.000	0.013	0.098
Supply mentions (Covid context)	60	0.450	0.675	0.000	0.000	1.000	3.000
Uncertainty mentions (Covid context)	60	0.950	1.171	0.000	0.000	1.000	5.000
Demand mentions (Covid context)	60	0.150	0.515	0.000	0.000	0.000	3.000
China mentions (dummy, non Covid context)	156	0.506	0.502	0	0	1	1
Panel B: Balance sheet variables							
Age	155	38.387	22.280	3.000	24.000	51.500	112.000
Size	155	11.163	1.411	8.020	10.124	11.923	15.372
Leverage	133	0.153	0.141	0.0001	0.030	0.247	0.562
Short-term borrowing ratio	133	0.468	0.370	0.000	0.124	0.858	1.000
Profit ratio	154	0.248	0.177	0.026	0.139	0.289	1.201
FX earnings ratio	132	0.286	0.325	0.0002	0.032	0.532	0.989
Cash ratio	155	0.063	0.089	0.0002	0.009	0.076	0.451
Trade receivables ratio	152	0.138	0.111	0.001	0.045	0.192	0.574
Collateral	154	0.371	0.236	0.00004	0.181	0.530	1.083
Inventories ratio	133	0.120	0.117	0.00000	0.038	0.154	0.676
Tangibles ratio	153	0.293	0.197	0.0002	0.123	0.448	0.872
Operating expenses ratio	155	0.766	0.153	0.123	0.711	0.867	1.017

Note: Size is defined as *log* total assets while age is in years. The remaining balance sheet variables are defined as: leverage is total borrowing scaled by total assets while short-term borrowings is short-term borrowing as a share of total borrowing, profit ratio is $PBDITA/total\ sales$, FX earnings ratio is $FXearnings/total\ income$, cash ratio is $cash\ and\ bank/total\ assets$, trade receivables ratio is $trade\ receivables/total\ assets$, collateral is gross fixed assets scaled by total assets, inventories are $inventories/total\ assets$, tangibles ratio is the sum of net plant and machinery, net land and building, and inventories, altogether scaled by total assets, and operating expenses are operating expenses scaled by total income.

Table 3 Selection bias check

Variable	Mean of excluded firms	Mean of included firms	p.value
Age	44.198	38.396	0.019
Size	10.715	11.181	0.001
FX ratio	0.182	0.286	0.002
ST borrowing ratio	0.367	0.468	0.013
Collateral	0.327	0.374	0.055
Tangibles ratio	0.330	0.293	0.069
Leverage	0.167	0.153	0.368
Profit	0.655	0.248	0.344
Trade ratio	0.060	0.236	0.349
Cash ratio	0.075	0.063	0.249
Trade receivables ratio	0.140	0.138	0.828
Inventories ratio	0.133	0.120	0.294
Operating expenses ratio	0.755	0.765	0.596
Interest coverage ratio	237.901	368.473	0.383

Note: The table provides a t-test of differences between balance sheet variables of the firms from the NSE $Nifty500$ for which earnings call reports are available (N = 196) relative to the others for which earnings call reports are not available (N = 304). Size is defined as *log* total assets while age is in years. The remaining balance sheet variables are defined as: leverage is total borrowing scaled by total assets while short-term borrowings is short-term borrowing as a share of total borrowing, profit ratio is $PBDITA/total\ sales$, FX earnings ratio is $FXearnings/total\ income$, cash ratio is $cash\ and\ bank/total\ assets$, trade receivables ratio is $trade\ receivables/total\ assets$, collateral is gross fixed assets scaled by total assets, inventories are $inventories/total\ assets$, tangibles ratio is the sum of net plant and machinery, net land and building, and inventories, altogether scaled by total assets, operating expenses are operating expenses scaled by total income, and interest coverage ratio is earnings before interest and taxes divided by total interest expenses.

Table 4 Differences in balance sheet characteristics of firms

Variable	Mean for control firms N = 96	Mean for treated firms N = 60	p-value
Panel A: Text-based variables			
COVID word count (raw)	0	3.083	0
COVID word count (scaled %)	0	0.023	0
Panel B: Balance sheet variables			
Age	35.011	43.733	0.014
Size	11.187	11.125	0.787
Leverage	0.149	0.158	0.734
Profit	0.256	0.234	0.445
FX ratio	0.300	0.265	0.514
Capital ratio	0.573	0.600	0.378
Cash ratio	0.071	0.049	0.117
Collateral	0.365	0.381	0.661
Trade receivables ratio	0.144	0.129	0.384
Inventories ratio	0.114	0.127	0.535
Short-term borrowings ratio	0.491	0.432	0.369
Tangibles ratio	0.263	0.340	0.016
Operating expenses ratio	0.758	0.780	0.340

Note: This table presents t-tests between firms that mention Covid-19 in January-February 2020 (treated), and those that do not (control). We only consider non-financial firms here. The control firms are in column 1 (N = 96); while the treated firms are in column 2 (N = 60). It shows that in terms of the balance sheet metrics, the two sets of firms are quite similar except for their age, and tangibles ratio. For variable definitions, please see table 2.

Table 5 Baseline results for CARs around the lockdown (1/2)

	Dependent variable:					
	CAR(-1,+1) around first lockdown (24/03/2020)					
	(1)	(2)	(3)	(4)	(5)	(6)
Firm mentions COVID dummy	−1.494	−2.929*	−2.974*	−3.365**	−3.919**	−3.246*
	(1.411)	(1.606)	(1.558)	(1.617)	(1.783)	(1.762)
log age		0.292	0.320	0.435	0.743	0.529
		(0.985)	(1.021)	(0.994)	(1.185)	(1.095)
log size		0.737	0.733	0.591	0.408	0.302
		(0.524)	(0.529)	(0.504)	(0.568)	(0.631)
Cash/TA			−3.000			
			(7.880)			
PBDITA/TA				8.896**		
				(3.907)		
FX earnings/Total income					−1.375	
					(4.399)	
Borrowings/TA						−3.921
						(7.325)
Cement & cement products		−1.507	−1.662	−1.144	1.383	−1.009
		(2.905)	(3.048)	(2.927)	(3.172)	(3.568)
Chemicals		5.787**	5.772**	5.412**	6.065**	7.174**
		(2.603)	(2.718)	(2.628)	(2.876)	(3.160)
Construction		−3.039	−3.078	−4.490	−3.104	−2.787
		(3.494)	(3.644)	(3.287)	(2.925)	(3.654)
Consumer goods		−0.829	−0.847	−1.016	−1.355	−2.633
		(2.977)	(2.922)	(2.902)	(3.035)	(3.619)
Fertilisers & pesticides		6.054*	5.915*	5.981*	6.360	5.776
		(3.228)	(3.206)	(3.291)	(3.919)	(3.693)
Healthcare services		11.017***	11.533***	8.423**	10.557***	7.269***
		(3.258)	(3.760)	(4.131)	(3.350)	(2.748)
Industrial manufacturing		0.533	0.486	0.218	−1.121	−0.066
		(3.408)	(3.430)	(3.241)	(3.573)	(3.578)
IT		2.587	2.839	1.443	4.214	3.901
		(2.858)	(2.961)	(2.864)	(4.102)	(3.667)
Media & entertainment		−6.130**	−6.221**	−8.126***	−6.286*	−8.731***
		(2.748)	(2.836)	(2.544)	(3.762)	(3.078)
Metals		−11.841***	−11.975***	−12.482***	−11.644***	−10.992***
		(3.570)	(3.580)	(3.339)	(3.622)	(4.093)
Oil & gas		−10.248***	−10.229***	−10.350***	−9.821***	−9.555***
		(2.924)	(3.019)	(2.770)	(3.190)	(3.581)
Pharma		2.589	2.596	1.647	2.867	2.672
		(2.734)	(2.825)	(2.718)	(3.725)	(3.094)
Power		−3.014	−3.171	−7.621*	−6.227**	−1.804
		(2.605)	(2.748)	(3.865)	(2.945)	(3.434)
Services		2.474	2.519	1.853	1.644	2.400
		(3.160)	(3.213)	(3.083)	(3.666)	(3.836)
Telecom		−6.096**	−6.243**	−8.605**	−4.052	−5.630
		(3.079)	(3.042)	(3.510)	(3.082)	(3.812)
Textiles		−10.822**	−10.972**	−11.097**	−11.367**	−10.505*
		(4.835)	(4.960)	(4.886)	(4.886)	(5.647)
Constant	−3.269***	−11.376*	−11.230*	−11.509*	−8.503	−6.393
	(0.843)	(6.604)	(6.645)	(6.074)	(7.198)	(7.652)
Observations	151	151	151	150	128	129
Adjusted R^2	0.0004	0.133	0.128	0.150	0.154	0.139
Sector FE	No	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01
Wild bootstrap standard errors clustered at firm-level in parentheses.

Note: The table represents the main results from equation 5. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. Column (1) represents the unconditional difference between the returns of "control" and "treated" firms. From column (2) onwards, we include sector fixed effects using NSE classification, as well as control for firm *log* age and *log* size. From column (3) onwards, we include balance sheet variables of interest one by one. Automobiles is the excluded sector throughout.

Table 6 Baseline results for CARs around the lockdown (2/2)

	Dependent variable:					
	CAR(-1,+1) around first lockdown (24/03/2020)					
	(1)	(2)	(3)	(4)	(5)	(6)
Firm mentions COVID dummy	-3.140^{**}	-3.513^{*}	-2.888^{*}	-3.447^{**}	-3.346^{**}	-3.899^{***}
	(1.533)	(1.918)	(1.691)	(1.723)	(1.597)	(1.455)
log age	0.479	0.703	0.557	0.256	0.516	0.776
	(0.997)	(1.057)	(1.129)	(0.979)	(0.979)	(1.163)
log size	0.763	0.253	0.621	0.647	0.482	0.548
	(0.647)	(0.636)	(0.568)	(0.516)	(0.517)	(0.669)
Inventories/TA	−22.597					−30.881
	(13.670)					(19.883)
St. borrowings/Borrowing		−1.657				
		(2.091)				
Tangibles/TA			−8.076			5.449
			(7.797)			(5.032)
Operating expenses/Total income				-11.323^{**}		7.067
				(4.832)		(14.012)
Trade receivables/TA					-16.808^{***}	−14.178
					(5.910)	(8.973)
Cash/TA						0.260
						(6.844)
PBDITA/TA						4.250
						(14.256)
FX earnings/Total income						−1.407
						(5.015)
Observations	129	129	149	151	148	110
Adjusted R^2	0.198	0.140	0.143	0.157	0.172	0.189
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01
Wild bootstrap standard errors clustered at firm-level in parentheses.

Note: The table represents the main results from equation 5. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. All columns include a constant and NSE-classification based sector fixed effects. We drop short-term borrowings from the full regression in column 6 as the data on that variable is patchy and leads the number of observations to drop to 96. Even in that case, the coefficient on the ”firm mentions Covid dummy” actually becomes larger both in magnitude and significance.

Table 7 Controlling for China mentions in non-pandemic context

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm mentions COVID dummy	−3.498**	−3.628**	−3.915**	−3.578**	−4.217***	−4.011**	−3.765**	−4.091**
	(1.678)	(1.656)	(1.686)	(1.773)	(1.576)	(1.719)	(1.630)	(1.794)
Firm mentions China in non-COVID context	1.217	1.367	1.194	−0.776	2.257	1.209	0.926	0.417
	(1.626)	(1.730)	(1.575)	(1.781)	(1.753)	(1.616)	(1.591)	(2.040)
Cash/TA		−4.065						−0.844
		(8.414)						(7.568)
PBDITA/TA			8.873**					4.981
			(3.886)					(14.878)
FX earnings/Total income				−1.077				−1.406
				(4.364)				(5.578)
Inventories/TA					−23.231*			−25.906
					(12.876)			(19.405)
Operating expenses/total income						−11.316**		7.875
						(4.716)		(15.385)
Trade receivables/TA							−16.689***	−14.983
							(5.838)	(9.446)
Observations	151	151	150	128	129	151	148	96
R^2	0.246	0.247	0.267	0.288	0.333	0.272	0.286	0.392
Adjusted R^2	0.130	0.124	0.147	0.147	0.202	0.154	0.167	0.150
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and size included	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:								*p<0.1; **p<0.05; ***p<0.01

Note: The table represents the main results from equation 6. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. All columns include a constant and NSE-classification based sector fixed effects and *log* age and *log* size are included as controls in all columns except column (1).

Table 8 Controlling for 'supply' and 'demand' mentions

	Dependent variable:							
	CAR (-1, +1) around first lockdown (24/03/2020)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm mentions COVID dummy	−4.070*	−4.213**	−4.351**	−4.592*	−4.558**	−4.405**	−4.210**	−4.824**
	(2.082)	(2.095)	(2.124)	(2.419)	(1.898)	(2.087)	(2.101)	(2.122)
Firm mentions supply in COVID-context	0.566	0.553	0.127	1.633	−0.576	−0.088	0.521	0.558
	(2.327)	(2.351)	(2.339)	(2.530)	(1.759)	(2.284)	(2.320)	(1.860)
Firm mentions demand in COVID-context	4.088	4.158	4.247	5.982*	5.634**	4.476*	3.005	7.155*
	(2.652)	(2.750)	(2.639)	(3.551)	(2.655)	(2.716)	(2.798)	(4.182)
Firm mentions China in non-COVID context	1.071	1.231	1.069	−0.916	2.146	1.089	0.816	0.523
	(1.690)	(1.750)	(1.691)	(1.754)	(1.724)	(1.654)	(1.681)	(2.011)
Cash/TA		−4.379						−1.691
		(8.237)						(8.071)
PBDITA/TA			8.778**					4.893
			(4.011)					(15.494)
FX earnings/Total income				−3.632				−6.009
				(4.337)				(6.093)
Inventories/TA					−24.168*			−26.276
					(12.918)			(18.421)
Operating expenses/total income						−11.344**		7.065
						(4.513)		(15.764)
Trade receivables/TA							−15.816***	−11.092
							(5.855)	(10.127)
Observations	151	151	150	128	129	151	148	110
Adjusted R^2	0.126	0.121	0.142	0.152	0.204	0.150	0.159	0.189
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and size included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01
Wild bootstrap standard errors clustered at firm-level in parentheses.

Note: The table represents the main results from equation 6. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. All columns include a constant and NSE-classification based sector fixed effects, and control for *log* age and *log* size.

Table 9 Controlling for sentiment of call reports

	Dependent variable:							
	CAR (-1, +1) around first lockdown (24/03/2020)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm mentions COVID dummy	−4.438**	−4.608**	−4.666**	−5.144**	−4.876**	−4.715**	−4.567*	−5.320**
	(2.223)	(2.273)	(2.361)	(2.607)	(2.003)	(2.255)	(2.348)	(2.425)
Net sentiment (baseline)	−3.777	−3.914	−3.334	−4.657	−3.104	−3.261	−3.700	−3.694
	(3.724)	(3.958)	(4.110)	(4.012)	(3.551)	(3.951)	(3.886)	(3.890)
Firm mentions supply in COVID-context	0.837	0.832	0.375	2.019	−0.332	0.160	0.785	0.970
	(2.524)	(2.443)	(2.469)	(2.634)	(1.919)	(2.450)	(2.551)	(2.068)
Firm mentions demand in COVID-context	2.789	2.820	3.098	4.597	4.546	3.346	1.741	6.108
	(3.103)	(3.100)	(3.101)	(3.685)	(2.929)	(3.116)	(3.232)	(4.206)
Firm mentions China in non-COVID context	1.075	1.252	1.074	−0.825	2.156	1.092	0.820	0.599
	(1.670)	(1.672)	(1.684)	(1.765)	(1.737)	(1.669)	(1.644)	(2.026)
Cash/TA		−4.844						−2.005
		(7.753)						(7.695)
PBDITA/TA			8.565**					6.010
			(4.010)					(15.339)
FX earnings/Total income				−3.969				−6.445
				(4.672)				(6.177)
Inventories/TA					−23.780*			−25.697
					(12.281)			(17.521)
Operating expenses/total income						−11.098**		8.598
						(4.576)		(15.346)
Trade receivables/TA							−15.734***	−10.731
							(5.899)	(9.934)
Observations	151	151	150	128	129	151	148	110
Adjusted R^2	0.125	0.120	0.140	0.152	0.201	0.147	0.158	0.186
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and size included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01
Wild bootstrap standard errors clustered at firm-level in parentheses.

Note: The table represents the main results from equation 6. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. The sentiment measure is based on valence-shifting bigrams using two sentences before and after a Covid-mentioning sentence. All columns include a constant and NSE-classification based sector fixed effects, and control or *log* age and *log* size.

Table 10 Controlling for 'uncertainty' mentions

	Dependent variable:							
	CAR (-1, +1) around first lockdown (24/03/2020)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm mentions COVID dummy	−1.952	−2.043	−2.285	−2.725	−2.895	−2.407	−2.244	−3.669*
	(1.817)	(1.867)	(1.827)	(1.961)	(1.792)	(1.791)	(1.820)	(2.051)
Firm mentions uncertainty in COVID-context	−6.083**	−6.659**	−5.801*	−5.488*	−5.540**	−5.575*	−5.688*	−4.827*
	(3.030)	(2.994)	(3.158)	(3.167)	(2.214)	(3.022)	(2.966)	(2.536)
Net sentiment	−7.997*	−8.657*	−7.389	−8.397	−7.154*	−7.182	−7.659	−7.410*
	(4.705)	(4.801)	(5.013)	(5.315)	(3.973)	(4.636)	(4.700)	(4.452)
Firm mentions supply in COVID-context	1.858	1.946	1.386	2.909	0.890	1.167	1.744	1.992
	(2.618)	(2.660)	(2.816)	(2.922)	(2.059)	(2.605)	(2.751)	(2.266)
Firm mentions demand in COVID-context	2.753	2.808	3.038	4.469	4.241*	3.254	1.833	6.126
	(2.701)	(2.643)	(2.783)	(3.396)	(2.481)	(2.686)	(2.875)	(3.891)
Firm mentions China in non-COVID context	1.108	1.450	1.103	−0.863	2.202	1.120	0.846	0.769
	(1.633)	(1.636)	(1.663)	(1.835)	(1.766)	(1.596)	(1.591)	(1.992)
Cash/TA		−9.272						−5.693
		(7.608)						(8.315)
PBDITA/TA			7.929**					8.070
			(3.727)					(15.180)
FX earnings/Total income				−3.710				−6.843
				(4.252)				(6.223)
Inventories/TA					−20.346*			−22.309
					(10.875)			(16.462)
Operating expenses/total income						−9.925**		9.220
						(4.151)		(15.219)
Trade receivables/TA							−14.077**	−8.780
							(5.863)	(10.358)
Observations	151	151	150	128	129	151	148	110
Sector SE	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.140	0.138	0.155	0.159	0.216	0.161	0.170	0.190
Age and size included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note:								*p<0.1; **p<0.05; ***p<0.01

Note: The table represents the main results from equation 6. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. All columns include a constant and NSE-classification based sector fixed effects, and control or *log* age and *log* size.

Table 11 Impact of the central bank's surprise policy announcement

	Dependent variable:		
	CAR (-1, +1) around central bank surprise announcement (27/03/2020)		
	(1)	(2)	(3)
Firm mentions COVID dummy	2.367**	2.024*	1.558
	(1.183)	(1.108)	(1.176)
Firm mentions uncertainty in COVID-context			0.901
			(1.444)
Cash/TA		−3.209	−2.604
		(6.152)	(6.232)
PBDITA/TA		2.585	2.458
		(8.674)	(8.911)
FX earnings/Total income		3.347	3.170
		(3.237)	(3.065)
Inventories/TA		15.107	14.613
		(9.445)	(9.745)
Operating expenses/total income		2.724	2.969
		(8.271)	(8.795)
Trade receivables/TA		−2.288	−2.456
		(7.557)	(7.740)
Observations	151	110	110
Adjusted R^2	0.025	0.042	0.033
Sector FE	Yes	Yes	Yes
Age and size included	Yes	Yes	Yes

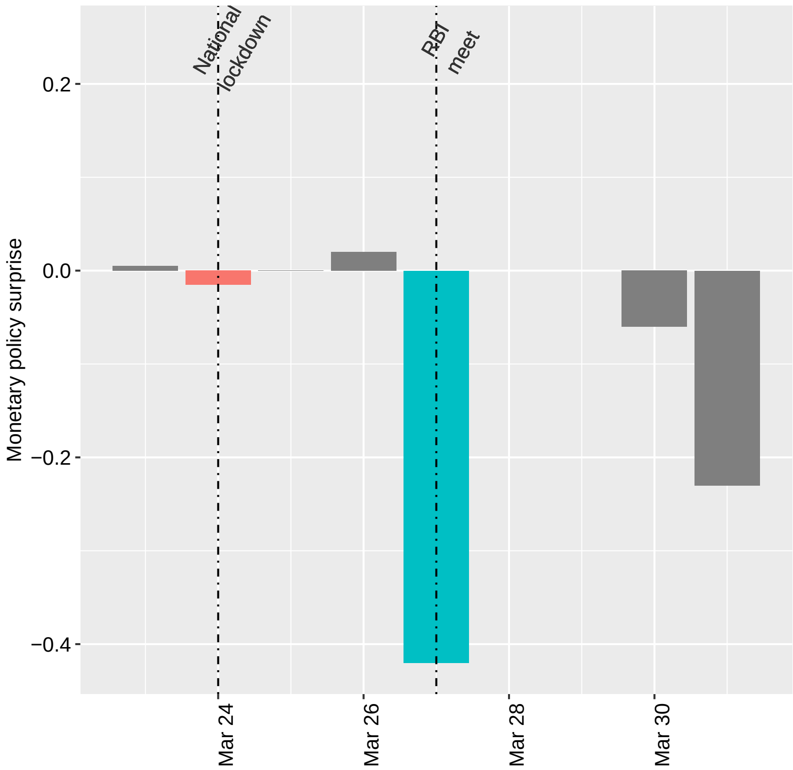
*p<0.1; **p<0.05; ***p<0.01
Wild bootstrap standard errors clustered at firm-level in parentheses.

Note: The table represents the main results from equation 6. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the Indian central bank's surprise policy package announcement on 27 March 2020, obtained from the market model in equation 4. All columns include a constant and NSE-classification based sector fixed effects, and control for *log* age and *log* size.

Appendices

A Figures

Figure 10 Monetary policy surprises around the national lockdown (24/03/2020) and RBI announcement (27/03/2020)



Note: The chart shows the daily change in the overnight indexed swap (OIS) rate between 23 March 2020 and 31 March 2020. We use this as the proxy for the monetary policy surprise as in Mathur and Sengupta (2019); Kamber and Mohanty (2018). If the daily change in the OIS rate is close to 0, there is no surprise. The monetary policy surprise on 27 March 2020 - which is a positive surprise - is the largest since the formal adoption of inflation targeting in October 2016.

B Tables

Table 12 Robustness check using alternate sentiment measure (1/2)

	Dependent variable:							
	CAR (-1, +1) around first lockdown (24/03/2020)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm mentions COVID dummy	−4.210*	−4.371**	−4.428*	−4.846**	−4.671**	−4.464**	−4.344**	−5.066**
	(2.200)	(2.197)	(2.265)	(2.451)	(2.021)	(2.235)	(2.192)	(2.221)
Net sentiment (alt.)	−1.238	−1.360	−0.701	−2.018	−0.952	−0.540	−1.190	−1.721
	(3.385)	(3.439)	(3.412)	(3.366)	(3.343)	(3.373)	(3.358)	(3.550)
Firm mentions China in non-COVID context	1.079	1.246	1.074	−0.871	2.156	1.092	0.824	0.566
	(1.689)	(1.659)	(1.643)	(1.718)	(1.785)	(1.605)	(1.610)	(1.980)
Firm mentions supply in COVID-context	0.703	0.703	0.207	1.870	−0.467	−0.025	0.653	0.810
	(2.441)	(2.502)	(2.474)	(2.623)	(1.957)	(2.509)	(2.575)	(2.200)
Firm mentioned demand in COVID-context	3.593	3.616	3.965	5.241	5.250*	4.258	2.531	6.543
	(2.907)	(2.995)	(2.824)	(3.790)	(2.931)	(2.884)	(3.157)	(4.411)
Cash/TA		−4.539						−1.884
		(7.990)						(8.106)
PBDITA/TA			8.723**					5.488
			(3.954)					(15.734)
FX earnings/Total income				−3.804				−6.224
				(4.489)				(6.121)
Inventories/TA					−24.095*			−26.196
					(12.812)			(18.036)
Operating expenses/total income						−11.288**		7.988
						(4.616)		(15.997)
Trade receivables/TA							−15.796***	−11.024
							(6.009)	(9.924)
Observations	151	151	150	128	129	151	148	110
Adjusted R^2	0.120	0.115	0.135	0.145	0.197	0.143	0.153	0.181
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and sector included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Wild bootstrap standard errors clustered at firm-level in parentheses.

Note: The table represents the main results from equation 6. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. The sentiment measure is valence-shifting cluster based using two sentences before and after Covid-mentioning sentences. All columns include a constant and NSE-classification based sector fixed effects, and control or *log* age and *log* size.

Table 13 Robustness check using alternate sentiment measure (2/2)

	Dependent variable:							
	CAR (-1, +1) around first lockdown (24/03/2020)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm mentions COVID dummy	-4.548^{**}	-4.768^{**}	-4.770^{**}	-5.216^{**}	-4.982^{***}	-4.835^{**}	-4.648^{**}	-5.438^{**}
	(2.197)	(2.191)	(2.276)	(2.465)	(1.921)	(2.156)	(2.269)	(2.244)
Net sentiment (alt.)	−3.604	−3.822	−3.224	-3.914^{*}	−2.846	−3.325	−3.280	−2.977
	(2.444)	(2.376)	(2.440)	(2.327)	(2.112)	(2.319)	(2.259)	(2.030)
Firm mentions China in non-COVID context	1.058	1.273	1.056	−0.801	2.128	1.077	0.806	0.676
	(1.654)	(1.708)	(1.596)	(1.715)	(1.779)	(1.673)	(1.659)	(2.009)
Firm mentions supply in COVID-context	0.372	0.342	−0.021	1.457	−0.666	−0.248	0.349	0.498
	(2.303)	(2.331)	(2.327)	(2.457)	(1.808)	(2.251)	(2.372)	(1.882)
Firm mentioned demand in COVID-context	2.271	2.255	2.610	3.979	4.136	2.788	1.385	5.629
	(3.234)	(3.214)	(3.062)	(3.852)	(2.928)	(3.052)	(3.389)	(4.459)
Cash/TA		−5.883						−3.499
		(7.622)						(7.700)
PBDITA/TA			8.327^{**}					5.155
			(3.812)					(14.646)
FX earnings/Total income				−3.540				−6.008
				(4.393)				(6.260)
Inventories/TA					-23.227^{*}			−25.056
					(12.466)			(18.227)
Operating expenses/total income						-10.999^{**}		7.167
						(4.558)		(14.848)
Trade receivables/TA							-15.305^{***}	−10.967
							(5.608)	(9.677)
Observations	151	151	150	128	129	151	148	110
Adjusted R^2	0.132	0.128	0.146	0.159	0.207	0.154	0.163	0.191
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and size included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01
Wild bootstrap standard errors clustered at firm-level in parentheses.

Note: The table represents the main results from equation 6. The dependent variable is always the cumulative abnormal returns of each firm at the end of the (-1,+1) event window around the first lockdown announcement on 24 March 2020, obtained from the market model in equation 4. The sentiment measure is valence-shifting cluster based using five sentences before and after Covid-mentioning sentences. All columns include a constant and NSE-classification based sector fixed effects, and control or *log* age and *log* size.

C Keywords used in the text analysis

Table 14 Keywords used in text analysis

Topic	Words
Covid-19	“covid”, “covid19”, “covid-19”, “corona”, “coronavirus”, “ncov”, “sarscov”, “virus”, “china situation”, “pandemic”, “epidemic”, “outbreak”, “disease”, “contagion”, “tragedy”, “infection”, “infection”, “lockdown”, “quarantine”, “self isolation”, “containment”, “social distancing”, “first wave”, “second wave”
Supply	“supply”, “supplies”, “supply chain(s)”, “imports”, “exports”
Demand	“demand”
Uncertainty	“uncertainty”, “uncertainties”, “uncertain”, “risk(s,y)”, “threat(s)”, “unknown”, “fear”, “exposed”, “unclear”, “possibility(ies)”, “doubt(s)”. “predict”, “unpredictable(ity)” “variable”, “chance”, “pending”, “variability” “instability”, “prospect”, “danger/dangers/dangerous”, “likelihood”, “queries”, “vary(ing)”, “probability(ies)” “tricky”, “fluctuate(ing)”, “reservation(s)”, “speculative(ion)” “dilemma”, “unsure”, “debatable”, “hesitant(cy)” “unstable”, “hazardous”, “unsafe”, “halting”, “hairy” “jeopardize”, “unforeseeable”. “question(s)” “difficult(ies)”, “concern(s,ed)”, “affected”, “effect” “wait and see”, “ambiguous”, “dubious”, “precarious”, “undecided”, “undetermined”, “unresolved”, “unsettled” “anxiety(ies)”, “have to see”, “worry(ies)” “remains to be seen”, “no idea”

Note: The table shows the keywords used in the text analysis of Indian firms’ earnings call reports. The uncertainty-related keywords are adapted from Sandile (2016). For more details, see section 3.

D Example of *uncertainty* mentions in the context of Covid-19

These sentences have been quoted from the January-February 2020 earnings call reports of "treated" firms which also mention uncertainty.

> It's difficult to really comment on it because no one knows, to be honest, the impact of coronavirus.

> However, it remains to be seen how the coronavirus will impact this, both for the Chinese economy and the global economy at large.

> So we don't know, you don't know and I don't know what is going to have an effect of coronavirus or all these kind of things.

> So that, we'll have to see how the coronavirus plays out.

> I think there are parts of the business that are sensitive to the uncertainty, especially interest rates, elections, global macro, of course, the new uncertainty that got introduced with global growth concerns around the outbreak with the China.

> We got to wait to see the coronavirus effect on us.

> On – really on virus, we just have no idea what's – it's going to depend how that virus plays out.

> Though we are very confident of pickup in domestic economic activities, led by revival in investment cycles, higher coal production, higher CapEx spending announced in the budget '21, but continued unseasonal range global slowdown and the recent coronavirus threat are posing risk in the near term.

> And as far as this China coronavirus issue is concerned, we, of course – I mean, it will be too early to predict anything.

E A short note on sentiment analysis

The earnings call held after the announcement of quarterly results of corporate firms provides a forum for open dialogue and expression of thoughts between senior management, market analysts and large shareholders of the firm. Audio data from such calls represents "unstructured data" that can be converted into text and analysed using a sentiment analysis approach.

E.1 Sentiment computation

As a first step in the sentiment analysis, we subject our earning calls to a standard text cleaning process which involves removal of stop words, white spaces, numbers and other irrelevant words. In the next step, each document or text corpus, firm-specific earning call report in this case, is divided into tokens. Tokens refer to a group of words, such as a single word or *unigram*, group of two consecutive words or *bigram*, a sentence or a paragraph (and so on). In our case, we break down each text corpus to the sentence-level for sentiment computation.

We use the lexicon-based method for sentiment computation as it is considered the most transparent, efficient and parsimonious method. We leverage the *Loughran-McDonald (LM)* lexicon developed specifically for research purpose in the domain of economics and finance (Loughran and McDonald, 2011).

For any text data, sentiment scoring can be done using: (a) *unigrams* approach; (b) *valence-shifting bigrams* approach; and (c) *valence-shifting clusters* approach. While the unigrams approach simply takes a weighted sum of all polarized words, we prefer the valence-shifting bigrams approach which is designed to evaluate the impact of valence shifting words that may negate, amplify or de-amplify polarized words in the document[1]. The valence-shifting clusters approach takes a slightly complex route to compute sentiments by using word clusters - maximum four before and two after - around polarized words in the text data.

At this stage, we calculate a raw sentiment score (RSS) defined as the sum of all polarized words, whether positive or negative, for each sentence in a given document using the Loughran-McDonald lexicon. We compute the sentiment score at the sentence level and then aggregate it at the document level. In the next step, the RSS is normalised by the total number of words in the document to arrive at the final sentiment score. By computing sentiments using the full text of the call transcript, we arrive at a quantitative measure of sentiments expressed by each firm during its earnings call. We refer to this as the overall net sentiment score (ONSS). The computational approach described above

[1] Valence-shifting keywords tend to negate, amplify or de-amplify the meaning of other words thereby changing the tone of the sentence. For instance, "this is not good" would be assigned a score of (+1) under the normal sentiment scoring approach. However, it would be assigned a score of (-1) due to the presence of a negating word "not" under our approach.

closely follows Algaba *et al.* (2020) More specifically:

1. For each firm-specific earnings call report, we use the LM lexicon to assign a sentiment score $RSS_{i,d}$ to each polarized word i occurring in document d.

2. Positive and negative words are assigned a sentiment score of (+1) and (-1), respectively.

3. The raw score is aggregated into an overall sentiment score (ONSS) such that $ONSS_d = \frac{1}{w_d} \sum_{i=1}^{Q_d} v_i * S_{i,d}$ where w_d represents the total number of polarized words and Q_d is the total number of words in each text corpus.

4. The term v_i captures the impact of valence shifters or keywords that may negate, amplify or de-amplify polarized words in the given document.

Finally, in order to capture sentiments expressed around Covid-19 pandemic during the earning calls, we adopt a hybrid clusters approach for sentiment computation. By design, this analysis is restricted to treated firms i.e., those firms which mention at least one keyword from our set of Covid-19 related words. After routine data cleaning, *sentences* occurring just before and just after a sentence containing a Covid-19 related keyword are extracted in the next step. We extract two sentences before and two sentences occurring after Covid-related sentences. The final step involves computation of a net sentiment score for the selected group of Covid-19 related sentences for each firm. For final sentiment computation, we adopt the valence-shifting bigrams as described above. We term this sentiment measure as Covid-19 net sentiment score (CNSS). For robustness, we create additional sentiment measures with three/five sentences and using all three of the unigrams, the valence-shifting bigrams and the valence-shifting clusters approach.