

Stress testing of firm level credit risk

Authors

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Abstract

This paper develops a method to estimate vulnerability of publicly traded firms to stress events using a bottom up framework. As an illustration of the method, we apply this method to publicly traded firms in India. Specifically, a given firm's exposure to overall market risk (measured using NIFTY 500 returns) and the Indian market's overall exposure to global market, forex and interest rate risk is used to estimate the sensitivity of firm level probabilities of default to changes in global market, foreign exchange rates and/or interest rates. Using this stress test methodology, the paper illustrates the impact of stress scenarios on corporate vulnerability - using the 2008 financial crisis and the 2013 taper tantrum as benchmark cases. The above stress test framework can be easily implemented for any combination of forex, market and interest rates scenarios to examine the impact of stress events on the probabilities of default of their obligors.

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1. Introduction

The Basel Committee for Banking Supervision suggests that there is substantial heterogeneity in bank stress testing practices across different countries.¹ Further, one important problem for implementing stress tests that is highlighted in report by the Basel Committee is that data and staff requirements for stress testing can be quite challenging for many countries across the world. To alleviate this issue, we propose a new method of stress testing for credit risk of corporates using market and accounting data that is publicly available. Our approach for stress testing has very minimal data requirements and also can be easily implemented.

A second advantage of our approach is that having publicly available risk metrics for the underlying obligors can serve as a transparent benchmark for underlying obligor risk, especially during a crisis. There is now a large body of literature that shows that banks strategically choose an internal risk model to underreport credit risk and minimize capital charges.² These incentives are more pronounced for weakly capitalized banks and in times of stress. Our approach mitigates this problem by setting natural limits on the extent to which banks can engage in such manipulation.

Our stress testing approach involves a three step approach – (1) In the first step, we estimate firm level default probabilities (pd, henceforth) using a standard reduced form model - key input variables being the market to book value of the firm and the closeness of its interest coverage ratio to 1. (2) In the second step, we estimate market level sensitivity to a set of risk factors (in our case, the factors being a foreign exchange depreciation, an interest rate increase and a global market crash). (3) In the third stage, we use each firm's stock market β and its interest coverage ratio to estimate a firm level effect of a market wide shock, where the shock could be in a combination of the risk factors listed above. Thus, with this approach, a common shock will (in general) have differential effects on each firm's probability of default due to different values of the shock on firm level market to book values as well as interest payments. An advantage of this approach is that it can easily accommodate shocks of a single factor (say a sudden foreign exchange depreciation) or multiple factors at the same time. Further, it can easily be modified to add additional country specific sources of risk, as estimation of risk sensitivity is done at the market level.

At a conceptual level, our approach to corporate vulnerability is similar to Duan et al. (2015). One key difference between their approach and ours

¹ [Basel Committee for Bank supervision: Supervisory and Bank Stress Testing: Range of Practices, December 2017.](#)

² See Plosser and Santos (2014), Mariathasan and Merrouche (2014), and Begley, Purnanandam and Zheng (2017).

are the model for credit risk that is used. In addition, we estimate firm level sensitivity to shocks whereas their approach involves estimating industry level sensitivity to macro-shocks.³ Additionally, all estimation is done using daily data due to which we are able to perform stress tests with a much shorter data series. On the other hand, an important advantage of their model is that they can estimate dynamic effects whereas our estimates are a point of time effect of a shock. Further, their underlying credit risk model is calibrated for over 100 countries across the world, while our model would need to be implemented for each country separately. Nevertheless, we believe that our approach complements their more sophisticated methods in terms of ease of implementation as well as significantly lower data requirements in terms of number of variables as well as the length of time series data, which are likely to be the case for emerging market countries.

We implement this methodology using Indian data. India is well suited as a test case for this approach for several reasons. It is a large emerging economy that has recently emerged from a large lending crisis. It was one of the most affected countries in the taper tantrum in terms of foreign exchange depreciation. Additionally, due to legal requirements, defaults above a certain amount are required to be publicly disclosed by law. This mitigates several data collection issues.

Our model is based on the reduced form approach used widely in credit risk prediction (Shumway (2001), Risk Management Institute (2016)). To minimize data requirements and attendant loss of firm for which we can estimate pd , we investigate and choose a small set of 3 variables for default prediction – which are the book to market ratio, a dummy if the interest to EBITDA of the firm is greater than 1, and liquidity (defined as cash to total assets).⁴ Even this extremely parsimonious model has a good degree of predictive power with the baseline model having around 82% area under the ROC curve, where parameters are estimated in a different period and tested separately in the forecasting period. As a comparison, using the forward intensity model developed by Duan et al. (2012), the RMI's benchmark model has an area under the ROC curve of 84.75% ([NUS RMI Credit Risk Initiative Technical Report, version 1, 2017](#), page 101). Interestingly, the above report also documents that the benchmark model for RMI performs relatively worse in China and India.

³ We circumvent some of the issues that come with noisy firm level sensitivities to macro-risk factors that possibly led to Duan, Miao and Chan-Lau (2015) to use industry aggregates by estimating firm level sensitivity to market return, and then the market sensitivity to other macro factors, as explained earlier in the introduction.

⁴ We find that the Merton's distance to default is not a robust indicator of future defaults after the inclusion of the book to market ratio when one uses a variety of sub-sample tests. Hence, it is not included as a predictor variable.

Our benchmark stress events are based on actual realization for the Indian Economy during the Financial Crisis of 2008 and the Taper Tantrum Crisis. Thus, our results should be interpreted as an increase in the probability of default at the firm or industry level if these stress events were to happen at the end of our sample period. Additionally, this framework also allows us to isolate the impact of each of these factors separately. To illustrate this, we examine what would happen to probabilities of default in the 2008 crisis if there were only a market crash and no effect on the treasury bill rates. Similarly, we also can examine the effect of a large foreign exchange depreciation without any impact on the market level or treasury bill rates.

Our main empirical results are that the market and risk free rate changes have differential impacts on the overall corporate vulnerability. For the 2008 crisis as well as the taper tantrum, risk rate increases have a non-linear impact on the top 15% percent of firms in terms of pd. Thus, a spike in the risk free rate disproportionately impacts these firms. While a crash in the market also has a differential impact on the increases in pd, this effect is more linear does not display the sharp kink in the increase in probability of default. Additionally, we analyze the impact of a ‘pure’ foreign exchange shock, which we define as a foreign exchange depreciation of 20% without any accompanying shock in the market or t bill market. We find that a movement of foreign exchange rates alone induces little movement in the probability of default. Thus, a key takeaway from our model is that controlling interest rate increases during a crisis (by infusing liquidity or other means) is more important than supporting asset prices or intervening in the foreign exchange market, at least from the view of minimizing the increase in credit risk of vulnerable firms.

We extend the above analysis to examine the effect of each shock on industry level vulnerability. We find that the two shocks have significantly differing impacts on the different industries, even though there is a large correlation between the industries that are impacted by each shock. Illustratively, while the 2008 crisis is found to be roughly five times as severe as the 2013 crisis in terms of pd change, this multiple varies significantly across industries. For instance, the retail industry is found to be was 12 times more vulnerable in the 2008 crisis vis-à-vis the 2013 crisis, which varies hugely relative to the unconditional factor of 5. Thus, given the ability of the stress test to measure differences in the actual pd increase across industries across shocks, the stress testing framework can be used as a regulatory tool to gauge industry level vulnerability.

To summarize, our paper develops a default probability model and a bottom up industry vulnerability model that can be applied with relatively little cross-sectional and time series data. A bottom-up approach to stress testing has

been recommended by the IMF and BIS and has been adopted by many regulatory authorities across the world. For instance, a bottom-up stress testing framework was implemented in Mexico starting in 2009 to assess the resilience of the banking system to provide measures of systemic risk. More recently, in 2017 the Central Bank of Brazil (BCB) initiated an annual bottom-up stress testing program to subject select Mexican banks (in particular the banks subject to the Internal Capital Adequacy Assessment Process (ICAAP)) to common macro-financial stress scenarios provided by the BCB. Furthermore, the Bank of Italy, the China Banking Regulatory Commission and the European Banking Authority have conducted multiple bottom-up liquidity stress tests to assess the vulnerability of their respective banking systems to liquidity shocks. Our paper provides an input into this process focusing on the impact of stress events on credit risk.

The paper is organized as follows: Section 2 describes the stress testing framework in more detail as well as the stress scenarios employed. Section 3 describes variables used for data analysis. Section 4 provides a detailed implementation of the stress testing framework for publicly traded firms in India. Section 5 provides the empirical results for the different stress scenarios including analysis of differential effects across different industries. Section 6 concludes.

2. Stress Testing framework

The stress testing approach that we proposed in the introduction is described in more detail here. Specifically, our model is a micro-stress test and follows the broad parameters of macro and micro stress tests as elucidated in Borio, Drehman and Tsatsaronis (2012). Figure 1 graphically depicts the steps in estimation our out model. At a first level, we estimate sensitivity (β 's) of the given market to the global market, forex risk and interest rates in the country (domestic interest rates). Next, we estimate the β of the given firm's equity with regard to the domestic market. Thus, any shock in the foreign exchange market or the global market impacts the firm's market value solely through its impact on the domestic market. Note that it is equally easy to incorporate other factors of risk into this step – one could easily envisage additional factors such as global interest rates, global liquidity, global price of risk and so on.

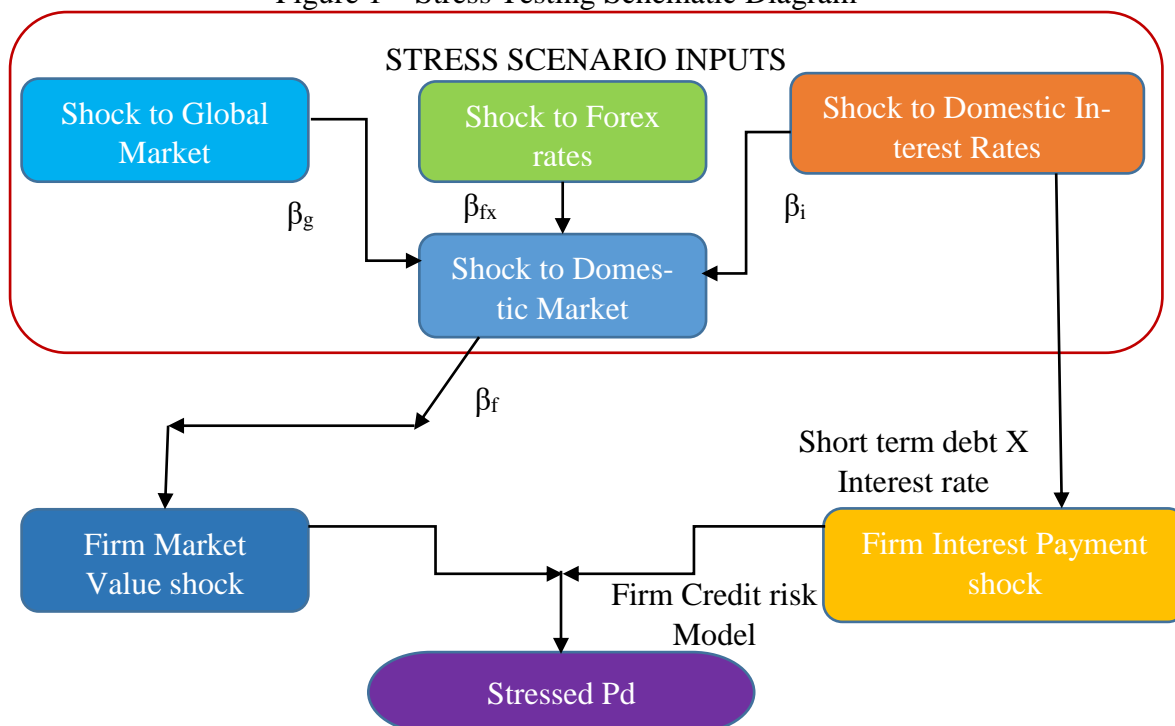
A natural question that may arise at this juncture is the rationale for an indirect effect of global markets or the foreign exchange rate on the given firm's equity. The justification for this modeling choice is not a-priori clear. An alternative approach could be to estimate a firm level β with regard to foreign exchange rates or any other risk factor? The justification for this choice is data

driven – in estimations, the direct effect of the global market or a foreign exchange change for most firms in India was insignificant, once the domestic market index is included in the estimation. Furthermore, the estimates of these β 's were highly variable which resulted in somewhat implausible estimates for shock effects, for the sample which had significant β 's.

Note that the model does not have any lagged or feedback effects – thus, a shock is applied at a point of time which results in an increase in the stressed probability of default in the same time period. While feedback effects are definitely valuable to model, one issue with estimation of such effects is a requirement of having cross-institution exposures, which is not easily available. In the case of corporate non-financial obligors, these cross-institution exposures are likely to be small.

Next, we posit that the interest rate payments have an additional independent impact on the likelihood of default – which is dependent on the level of short term debt of a given firm. Specifically, we posit that the interest payments of all the short term debt of the firm is immediately repriced (this is equivalent to assume that it is fully floating rate). Thus, the increase in interest rates causes an immediate increase in interest payments for the firm, which may potentially cause a cash flow liquidity problem. Thus, domestic interest rates have two possible channels of impacting firm credit risk – via impacting the overall domestic market, which in turn impacts firm value and therefore its credit risk, and via impacting firm's interest payments due to repricing.

Figure 1 – Stress Testing Schematic Diagram



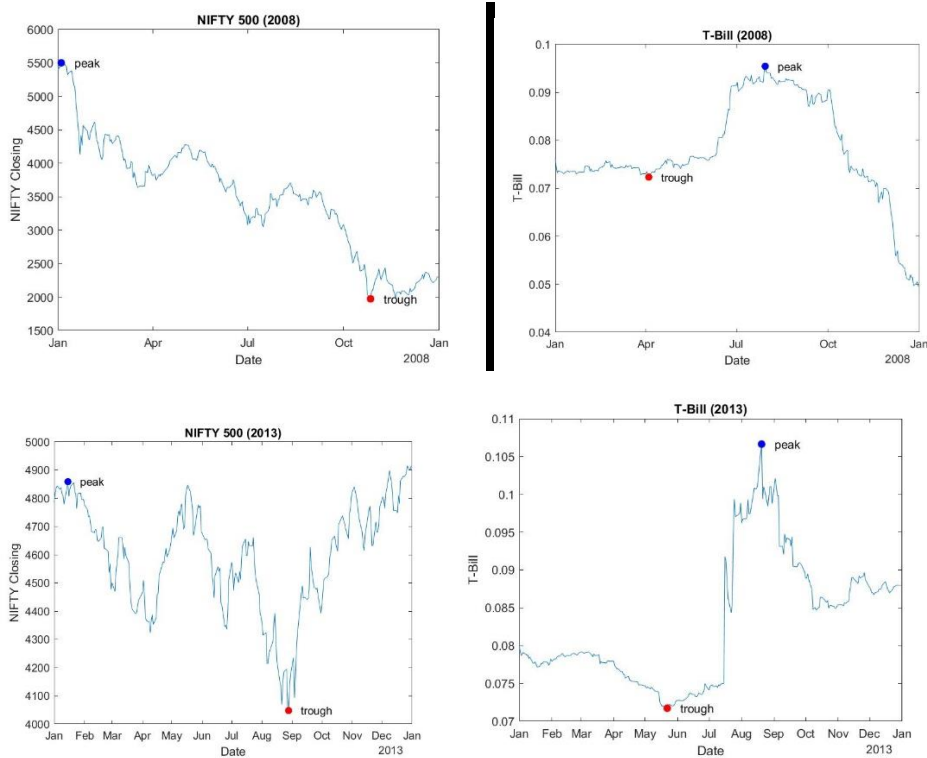
Finally, we estimate a credit risk model that has these two variables : market value of the firm and interest payments as inputs, in addition to all other inputs that are found in normal credit risk models. As such, default prediction models in structural and reduced form (Altman, 1968; Merton, 1974; Ohlson, 1980; Shumway, 2001) use these either directly variables or in a transformed form with other variables as inputs for prediction of credit risk.

To summarize, our model estimates a set of β 's which determine how a given stress scenario impacts firm specific market value and firm specific interest payments. The stress scenarios could be a combination of global and local market rate movements, local interest rate movements, and the exchange rate of the given country. Data for the baseline probabilities of default are estimated as of a given date, using the most recent market and accounting data available for the given firm. Based on the stress scenario, a new probability of default is estimated. The difference between distribution of the baseline pd and the new pd for the given stress scenario is the primary variable of interest, as this is a measure of how the overall economy reacts to a given shock.

2.1 Stress Scenarios

Next, we provide details on the stress scenarios. As our first benchmarks, we take the Indian market and Indian T-bill responses to the credit crisis of 2008 and the Taper Tantrum of 2013. In both cases, we use identify peak (prior to the crisis) to trough (after onset of crisis in the same year) movements for the NIFTY 500 index to identify the maximum negative market return for the given crisis. For the interest rates, we similarly measure the lowest Indian 1 year T Bill prior to the crisis (the trough) and the highest Indian 1 year T bill rate after the onset of the crisis.

Figure 2: Behavior of NIFTY 500 and T-Bill in 2008 (top row) and 2013 (bottom row)



We take each of the above figures and compute the maximum change in each variable from its peak to trough value (for the market value of the index) and trough to peak value (for the treasury bill). We take these realized changes in market values and treasury bill rates as the two historical scenarios for the 2008 and 2013 shocks. The shock magnitudes are presented in Table 1 below.

Table 1: Historical Shock Scenarios

Description	Taper Tantrum - 2013 Shock	Lehman - 2008 Shock
Indian Market Price Shock	-17%	-64%
Interest Rate Shock (Indian T-Bill)	3.49%	2.3%
Global Shock (S&P 500)	-0.56%	-48%
Forex Shock (INR/USD)	22.8%	22%

As a basis for comparison, we also present the peak to trough values for the movement of the foreign exchange rate for India in terms of Indian Rupees per US dollar and the movement of the S&P 500.

The method we use is also amenable to isolate the effect of individual shocks. To illustrate this, we examine the impact of shock only to the market value of NIFTY500, i.e., a stress scenario where the NIFTY index crashed without any accompanying rise in financing costs due to increase in the treasury bill rates. As another illustration, we examine the effect of a 20% depreciation in the foreign exchange rate, which approximately equals the magnitude of the foreign exchange return during the 2008 and 2013 crisis. Thus, this hypothetical scenario allows us to examine the effect of a forex shock without any other accompanying rise in treasury bill rates.

3. Sample and Variable Construction

In this section, we describe the construction of the data sample providing detailed information on construction of the variables as well as treatment of missing data. Data regarding listed firms (both accounting and financial data) and firm level defaults is collected from Prowess and CIBIL. Prowess is a database collected by the Center for Monitoring of the Indian Economy (CMIE). Prowess is the Indian equivalent of the CRSP and COMPUSTAT databases in the US. It has extensive accounting and stock market data and is widely used in academic studies. For default indicators, we use the CIBIL data (an Indian subsidiary of TransUnion). An important advantage of this database is that all defaults above a certain threshold are mandatorily reported to CIBIL, which in turn, makes these publicly available on a quarterly basis. Next, we describe in detail the construction of each of the variables used in the empirical analysis.

3.1 Stock Market and Accounting Data

The accounting information for a given financial year for firm i is assumed to become publicly available one day after the Annual Report for the relevant financial year is signed and this date is named as the disclosure date. If the disclosure date is not available, then it is assumed to be the 1st of September of the calendar year. Since the financial year in India runs from April 1 to March 31, this method assumes that the financial statements become publicly available 5 months after the end of the financial year for those company year observations where the actual disclosure data is not available. To ensure that we only use information that is publicly available as of a given date, when we merge the stock market data with the accounting data in a given calendar year, the pre-

disclosure period is matched with accounting data from year $t-1$ while the post-disclosure period is matched with accounting data from year t . This method of matching ensures that we do not have any look-forward bias.

All observations prior to 2009 are dropped as several variables we need for the empirical analysis are not available prior to this date. Observations for which total assets or market capitalization is missing are dropped. All unlisted firms are dropped as this study only focuses on prediction of stress for listed firms. Lastly, we delete all duplicate values based on Prowess company code and the date as on end of financial year i.e. if the financials of firm i have been reported multiple times for a given financial year in Prowess, only the first instance is kept (there is no variation in the data reported across duplicate observations).

Daily stock market data is downloaded from Prowess. Market capitalization of firm i on date t is calculated using the closing prices on the Bombay Stock Exchange (BSE) or National Stock Exchange (NSE). If a firm is listed on both the BSE and NSE, then the market capitalization is based on the average of the closing prices at both the exchanges. If a closing price is not available for a given day for a given firm, the observation is dropped. All values of market capitalization are in INR million. Duplicate values are dropped based on the Prowess company code and trading date i.e. if the market data for firm i has been reported in Prowess multiple times for a given trading day, we keep only the first observation (there is no variation in the data reported across duplicate observations). There are total number of 7970 publicly traded firms in the Prowess database that have stock market capitalization available and there are a total of 43070 firms that have total assets available in any one year. When we merge firms with stock market and accounting data available for analysis, this results in a total of 5064 firms. Out of these, a total of 391 firms have data for only 1 year and therefore are dropped from the analysis. This results in a final sample of 4673 firms.

3.2 Firm Level Default data

CIBIL and Watchout Investors publish quarterly data on those firms that have defaulted on their debt payment obligations. While Watchout Investors obtain their information from a variety of public sources, Government of India regulations require banks to mandatorily disclose any corporate or individual defaulter where the aggregate amount of default is greater than Rs. 1 crore (Rs 10 million). These firms constitute the sample of firms that have defaulted in the Indian economy in each quarter in calendar year t . This data is

scraped from the CIBIL website (<https://suit.cibil.com>) and the Watchout Investors website (<https://www.watchoutinvestors.com>) using a python program. The python program works through a python controlled web driver to scrape default data from each website. The CIBIL data repeatedly reports a firm as defaulted in every quarter after its default. We only use the first instance of reported default and in all subsequent time periods, the firm is not considered as part of the empirical estimation.

As the panel regression estimation is done on an annual basis using independent variables as of January 1, we create a default dummy for each firm for each calendar year based on the quarterly data. As mentioned above, once a firm defaults in the calendar year, it is not used in the estimation in subsequent years. Thus, each firm will have a default dummy equal to 0 for each year up to the year of its default, 1 in the year of default, and default dummy set to missing after this year. Thus, the actual date of default in a given year is not relevant to our estimation method.

The companies in the firm level default database are mapped to the companies covered by Prowess based on company name (given in the Prowess Identity database) using string matching. To facilitate string matching, we clean each company name by changing all the names to lowercase, removing all punctuation, all articles, ownership prefixes (pvt., ltd., limited, partnership, sole proprietorship, individual account, M/S, corporation), special characters (ex: %, &), profession identifiers (ex: exporter) and country name (i.e. India). This assigns a Prowess company code to each firm in the default database. We then delete all duplicates based on the company code and quarter (at the most a company should have only one default occurrence per quarter).

There are a total of 4240 distinct firms that had defaulted from the scraping exercise that are matched to the Prowess database. Out of these, 3879 defaults correspond to unlisted firms and 361 firms are those that are publicly traded. This is the final default data that is used to estimate the pd model. The final sample consist of 4673 distinct firms with 35096 firm year observations.

3.3 Missing data

As one of the goals of this study is to have the largest possible sample for predicting stress in the overall economy, we fill in missing values using most comparable size industry level peers in the same year. Prowess has a total of 194 industry classifications. Since one of the important purposes of this study is to undertake stress testing from a central bank perspective, we map these industry categories into a broader classification based on Reserve Bank of India.

Specifically, we use the industry classifications provide in the Financial Stability Report of RBI. This divides the total industries into a total of 18 sectors. The actual mapping is provided in Appendix A of this report. One important advantage of having a broader categorization is that having a larger set of firms in the industry significantly helps in finding a comparable set.

The details of the procedure is now described. When a given variable is not available for a firm, we examine if there are 20 non-missing firm observations for the given variable in that year and the same industry as the firm with the missing value. If there are 20 observations available, we choose a reference firm that is closest in size (total assets measured by the most recent balance sheet) to the firm with the missing value. Relative to this reference firm, we choose 5 firms above and 5 firms below that are closest in size. We choose the median value of these firms for the given variable of interest. Thus, if for firm i , liquidity is missing, we choose the median liquidity for 11 firms in the matching set.

If 20 valid (i.e. non-missing) observations are not available at the firm level within the industry to which firm i belongs in calendar year t , then the missing value of the relevant variable is replaced by the median value of the industry for the year t . If no valid (i.e. non-missing) observations are available for the concerned variable for the industry to which firm i belongs in calendar year t , then the missing value is replaced with the median value of the concerned variable for the entire calendar year t for the full sample.

Based on this method, there were a total of 285 missing data observations that were filled in for the interest to EBITDA ratio and 5925 observations for the total debt. No observations were missing for the liquidity ratio. These are relatively small number of observations when compared to the sample size of 35104 firm year observations. For computation of other variables (Altman's Z score, the Ohlson's O score).

4.0 Implementation of the model for the Indian corporate sector

We next describe actual implementation of the model described above for the Indian corporate sector. We start from the bottom of Figure 1 (the default model) and work our way upwards.

4.1 Default Model

Our principal model for default prediction is quite parsimonious – we seek to have variables that will reflect a firm’s vulnerability to interest rate shocks as well as its market value. We started with a set of variables used in the model by Shumway (2001) as well as the model by Duan and Tao (2012). In addition to this, we also construct the Altman’s Z score, the Ohlson’s O score and Merton’s distance to default. Unfortunately, if we use all of these variables, the data sample shrinks quite significantly. Since the goal of this exercise is not to derive the best possible credit risk model but rather estimate the effect of market wide shocks on firm level default probabilities, our choice of variables is motivated by this end goal – specifically, given the stress testing framework in Section 2, we need one variable that captures changes in equity market value of the firm and another that measures interest rate vulnerability.

For both of the above, one possible candidate would be the market value of the firm itself as well as an interest coverage ratio, both of which have been shown to be significant in past studies. However, for both of these variables, we find that a transformed version of these variables perform quite well in terms of prediction power for our given sample.

Take for example the EBITDA to interest expense ratio. A company whose ratio moves from 10 to 5 probably has a slight increase in corporate default. In terms of our variable used (interest to EBITDA, this variable moves from 1/10 to 1/5. In contrast, a company whose ratio moves from 2 to 1 has a large increase in corporate default. In fact, in our empirical tests, we find that the threshold of 1 becomes quite important, and once a dummy for reaching this threshold is included in the model, the interest to EBITDA variable becomes insignificant, suggesting that the threshold is more predictive relative to the continuous variable.⁵

Our use of the book to market ratio is motivated a large literature finance that uses this variable as a predictor for future returns (Fama and French, 1992). While Fama suggests that this variable proxies for distress risk, others such as Campbell, Hilscher and Szliiyagi (2007) do not find evidence that distress risk is priced in the cross-section. The question on whether distress risk is priced in the cross-section of stock returns, while extremely interesting, is not the subject of this paper. Rather, in relation to using log of market value as in Shumway (2001), this variable may also act as a reasonable predictor of default.

⁵ We also experimented with including the interest to PBITDA ratio above 1 alone, i.e., for companies in distress. This also does not have any explanatory power.

The above two variables are the principal variables of interest for the stress testing as this the stress events will finally impact the probability of default through either one or both of these variables. A detailed definition of all other variables used in default prediction along with a description of the default model is provided in Appendix B. Once all variables are created, we create a yearly panel with all independent variables measured as of as of the beginning of the year, i.e., on January 1. Recall from Section 3.1 that a firm that defaults in year t (from Jan 1 to Dec 31) has a default indicator of 1 for that year. This will be the dependent variable that will be predicted based on the beginning of year data. Our model is estimated using a logistic regression. The estimates are given below in Table 2, model 1.

To avoid a look forward bias, we estimate the default model from 2009 to 2016 (termed the training period). We then use the coefficient estimates from this regression to estimate default probabilities and the change in default probabilities at the firm level in 2017-2018 (the testing period). The prediction power of the default model in the testing period provides a validation of our default model.

To compare the performance of our model with other well known models of default prediction, we also compute the Altman's Z score and the Ohlson's O score using additional data variables.⁶ We present the model performance in the training and testing periods using these additional dummy variables based on these two scores as controls. The use of dummy variables based on these two variables is required as these variables have a non-linear effect on default likelihood. In the case of the Z score, we create a dummy variable that takes a value of 1 if the Z score is below 1.8 and 0 otherwise. In the case of the O score, we create a dummy variable that takes a value of 1 if the O score is below 0 and 1 otherwise. Created this way, a Z score dummy or an O score dummy of 1 implies a higher degree of credit risk relative to the value of 0. Note that if one included the Z score or O score directly, this does not impact the performance of the baseline model. In addition to the above, we also include a dummy for high leverage firms and an additional control for firm size in models (2) and (3).

The prediction accuracy of all models, as measured by the area under the Receiver Operating Characteristic (henceforth, prediction accuracy) is 80.43% for the baseline model. If one adds additional controls (leverage, size) along with Altman Z score, the prediction accuracy increases to 81.44%. Similarly, for if one includes the O score, the prediction accuracy is 82.00%.

⁶ Appendix A provides the details of the computation of these scores as well as the definition of all other variables used in the augmented default prediction models.

Thus, the inclusion of well-known credit risk controls does increase the prediction accuracy slightly but not by a very large amount.

Table 2: Default Model

	(1)	(2)	(3)
Intercept	-9.16***	-9.95***	-10.50***
Liquidity	-5.15***	-5.83***	-5.42***
Interest to EBITDA > 1	0.78***	0.86***	0.85***
Book to Market ratio	5.94***	5.01***	4.85***
High Leverage Dummy		0.74***	0.75***
Size		0.20***	0.18***
Altman Z-Score Dummy		-0.13	
O-Score Dummy			0.88***
Training Period ROC	80.43%	81.44%	82.00%
Testing period ROC	84.08%	85.84%	85.81%
Training period observations	27874	27874	27874
Testing Period observations	7222	7222	7222

Note: ***, **, and * indicate significance at 1, 5, and 10 per cent levels, respectively.

However, if one adds these additional controls, several of our variables – interest to EBITDA and market value also enter through other control variables, resulting in lack of a clean identification of the marginal effect of each of these variables on the default likelihood. Since the principal aim of this paper is not to derive the best possible credit risk model, but to have a clean interactive effect of stress events, we continue to use our baseline model for the remainder of this paper.

It is important to note that the way the baseline model is set up, an interest rate shock matters only for firms that are close to value of interest to EBITDA close to 1, as these firms are those that would switch from 0 to 1. A firm that has a ratio far below 1 or above 1 prior to the shock will not be impacted.

Note also that the testing period prediction ability for all 3 models is higher than the training period which suggests that the model has good out of sample prediction power. This is likely due to a change in the regulatory recognition of defaults in this period. Specifically, the Reserve Bank of India conducted a detailed asset quality review of several banks in December 2015. Prior to this period, it was believed that several large firms that had actually

defaulted were not declared to be in default by extending the terms of the loans and reducing repayment, a process well understood and widely known as evergreening or zombie lending. Post audit, RBI used its regulatory power to force banks to declare certain large borrowers to be in default. In the fiscal years 2015-2018 period, the gross NPA declared by Indian banks increased from 4.3% to 11.5%.⁷ Thus, firms which had truly defaulted in an economic sense were also being classified as defaulted in a regulatory sense in the testing period, which may account for the increase in predictability.

Another alternate way of examining the efficiency of this rather parsimonious default model is to consider the degree to which it is able to forecast defaults and how this compares to rating agencies in India. We illustrate this using the predicted probability of default and comparing it to ratings of the firm for a period of 8 quarters before default. To make the corporate default PDs and credit ratings comparable, we carry out the normalizing procedure described below.

For the Corporate Default PDs, we calculate the average PDs of all defaulting firms for quarter 0 and each quarter before default. Further we measure the Relative PDs (RPD_t) as follows

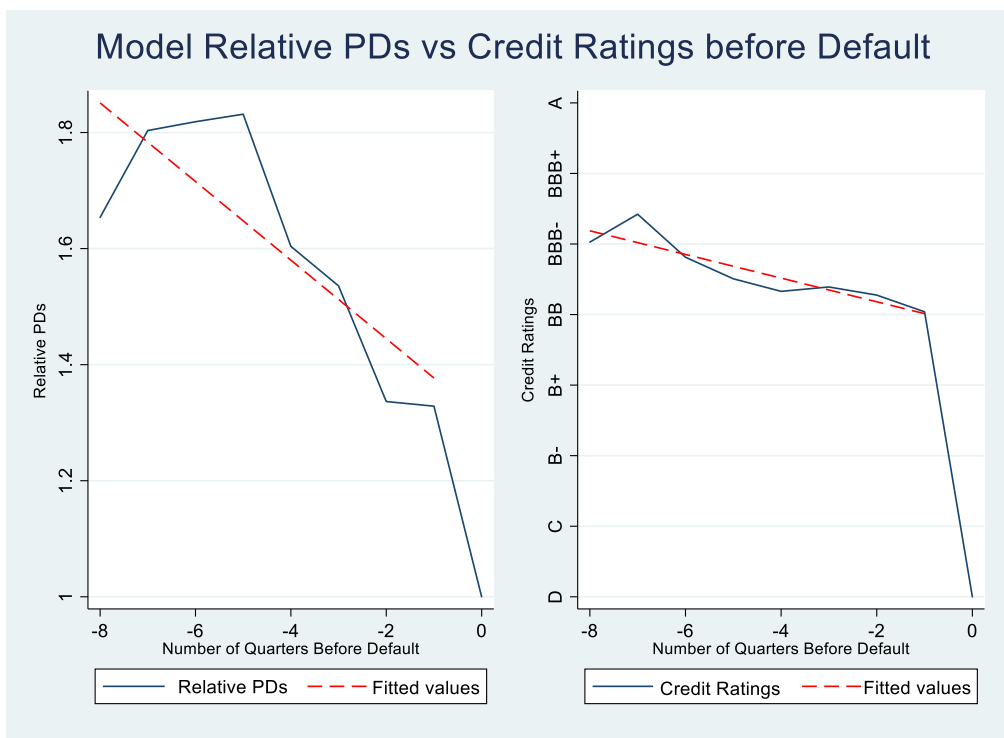
$$RPD_t = \frac{PD_{t=0}}{PD_{t=0-i}} \quad \forall i = 1, 2 \dots 8$$

Thus, we have Relative PDs up to 8 quarters (2 years) before default. Quarter 0 is the quarter of default and at the default quarter RPD_t equals 1.

For the credit ratings, we calculate the average credit rating awarded by credit rating agencies to the defaulting firm for the 8 quarters before default. We do so by mapping each credit rating in each quarter for a firm i (if multiple ratings are available, we keep the lowest rating) to the numbers from 1 to 20, where the number 20 corresponds to a AAA rating and the number 1 corresponds to 1. We then take the average across firms for all quarters up to 8 quarters before default to compute a relative rating for each quarter prior to default.

⁷ See "[Asset quality review may have permanently reset banking system NPA](#)," Business Standard, June 27, 2019.

Figure 3: Corporate Default Model Relative PDs vs Average Credit Ratings before Default



For companies that defaulted, the change in rating from 8 quarters prior to default to one quarter prior to default was only 1 notch, from BBB to BB-. However, in the last quarter prior to default, ratings were moved by several notches, i.e., a rating cliff. In contrast, the relative probability of default starts moving almost 8 quarters prior to default, thus showing that the default model proposed in this paper can add significant value relative to credit ratings.

To summarize, the model of corporate default that we use has a high degree of predictive power and can lead rating agencies in terms of early warning of default. Most importantly, it has the ability to easily compute the impact of macro shocks on firm specific default probabilities, which is the principal goal of this study.

4.2 Computing firm sensitivity to the market (β_f)

As the second step of the stress testing framework in figure 1, we estimate firm level β 's with respect to the Indian market, where we use the NIFTY 500 index as the benchmark for the Indian equity market. To do this, we estimate a firm by firm regression for the period January 2015-October 2018 for each firm having at least 252 days of trading data in the period January 2015-October 2018. For firms for which β_f cannot be computed (i.e. the firms lacking 252 days of trading data), we implement a replacement algorithm to replace the missing β value similar to that described in Section 3.3, the only difference being that firms are matched on market value of equity, whereas in the previous section, they were matched on book value of assets.

4.3 Computing Indian market sensitivity to the risk factors

As the last step prior to computing the effect of the stress scenarios, we need to compute the responsiveness of the Indian Stock market to each of the stress input factors (forex, global markets and the Indian Treasury Bill rate). To compute this, we regress the Indian Stock market return on date t on the US market return on date $t-1$, the percentage change of foreign exchange rate measured in Indian Rupees per US dollar, and the change Indian 1 year T bill rate for the time period January 2012- October 2018 using daily data. Note that we lag the return on the US market by $t-1$ as the US market trading hours start after the close of trading in the Indian market. This yields the values of the factor sensitivities (β_g , β_{fx} , β_i) towards the global market, foreign exchange rate and local government interest rate respectively. The results are given below in Table 3.

Table 3: Coefficients from Indian Market Estimation

	Estimate
Intercept	0.00***
β_{fx}	-0.75***
β_i	-1.11***
β_g	0.21***
Adjusted R ²	0.2198
No. of Obs.	1561

As estimated above, a positive foreign exchange return (corresponds to a depreciation in the Indian Rupee) has a strong negative impact on the Indian

market. Increases in the T Bill rate have a strong negative effect on Indian markets and global markets are positively related to Indian markets. An important point to note is that the foreign exchange rate has the largest marginal effect on the Indian market – if we take the hypothetical stress scenario with a depreciation of 20% for the Indian Rupee, this will lead to a predicted market reduction of the NIFTY500 of around 15%. In contrast, an increase of 200 basis points in the interest rate is predicted to reduce the NIFTY500 by around 2.22% and a reduction of 20% in the US S&P500 index is predicted to reduce the NIFTY500 by around 4%.

4.4 Computing firm level responses to shock scenarios

Finally, we come to the last step of estimation of the stress testing procedure – computing firm level effect of a given stress scenario. There are two primary drivers of stress in our framework – a lower market value and an increase in the interest payments (due to a change in T bill rates) which makes some firms with an interest to EBITDA ratio close to 1 become vulnerable.

Recall from Section 2 that there were two actual stress scenarios (the 2008 and 2013 shocks) and hypothetical stress scenarios based on movements of the global stock market, forex rate and T bill rate respectively. We first elaborate on the estimation method using a hypothetical shock:

- (1) **Shock effect on NIFTY500:** Compute the effect of the shock on NIFTY500 return using the coefficients from Table 2 above. Since the impact of these shocks is linear in the proposed framework, the impact of multiple shocks is just the product of the magnitude of the shocks multiplied by the corresponding β .
- (2) **NIFTY500 shock effect on firm market value:** Compute each firm's return for the given shock scenario by computing $\beta_f \cdot \text{NIFTY500 return (shock)}$. The change in market value of the given firm is simply $\text{Market Value (pre-shock)} \cdot \beta_f \cdot \text{NIFTY500 return (shock)}$. Compute the post-shock market value of the firm by taking the sum of the pre-shock market value and the change in market value due to the shock, which is negative by construction. Compute the Book to Market ratio (post-shock) as the ratio of the

pre-shock book value of the firm and the post-shock market value of the firm.⁸

One empirical challenge that arises when implementing these stress scenarios is that stocks with a high β may end up with a negative market value for a large enough magnitude of shock. To preclude this, we limit the negative return for any shock to -80% so that firm's market value does not become negative after the shock. This condition will become binding that for any stock with an estimated β of 1.25 or above for the 2008 shock, as such stocks will have a return of more than -80%. To the extent that this assumption is violated, this implies that increases in probability of default predicted by our model are lower than the actual increases in probability of default.

- (3) **Shock effect on interest payments:** Compute the change in interest payments of the firm as the product of change in the Indian T bill rate for the stress scenarios multiplied by the total short term debt of the firm. The post-shock interest payments is computed as the sum of the pre-shock interest payments and the change in interest payments. By construction, the change in interest payment is either positive or zero (for firms with no short term debt). The interest rate shocks are positive by assumption.
- (4) **Interest Payment effect on Interest to EBITDA ratio:** Compute the Interest to EBITDA ratio (post-shock) by taking the ratio of the interest payments (post shock) and the EBITDA (pre-shock). The assumption here is that the EBITDA of the firm does not change immediately after the shock.⁹ Compute the Interest to EBITDA >1 dummy variable for each firm in the post-shock period. As should be evident, this dummy will change only for firms that have an interest to EBITDA value in the pre-shock period close to 1 and have a relatively larger amount of short term debt in their capital structure.

⁸ This assumes that the book value of the firm does not change due to the shock. Since our framework for stress is a point in time analysis, accounting values for the book values of assets would not change.

⁹ To the extent that this is violated, i.e., the EBITDA of the firm changes negatively after the shock, this would imply that our calculated interest to EBITDA ratio (post-shock) is lower than the true value of the interest to EBITDA ratio, after accounting for the change in EBITDA. Thus, the responses here can be viewed as a lower bound on the changes in probability of default due to increases in the interest payments.

- (5) **Pre-shock Probability of default:** Compute the baseline fitted probability of default for each firm prior to the shock $\{\widehat{pd}_f(\text{preshock})\}$. This is based on the logistic model in Section 4.

$$\widehat{pd}_f(\text{pre-shock}) = \frac{e^{\beta_0 + x_f(\text{pre-shock}) * \beta}}{1 + e^{\beta_0 + x_f(\text{pre-shock}) * \beta}}$$

where the coefficient values for the β 's are based on the values in Table 2 and the $x_f(\text{pre-shock})$ are the pre-shock values of liquidity, book to market ratio and interest to EBITDA for the given firm.

- (6) **Post shock probability of default:** Compute each firm's fitted probability of default after the shock, $\widehat{pd}_f(\text{post-shock})$, by using post shock values of book to market ratio from step 2, and post shock values of the interest to EBITDA dummy from step 4. Note that the liquidity value does not change due to the shock by assumption.

For the 2008 and 2013 actual stress scenarios, the only step that differs is step 1, as we do not need to estimate the effect of the shock on NIFTY500 as the actual magnitude of the NIFTY return is directly observed in the data. Thus, instead of step 1, we use the realized magnitudes of the shock in the NIFTY500 for these two crises (-64% and -17% for the 2008 and 2013 crisis respectively) and derive the change in market value at the firm level as explained in step 2 onwards.

5. Results of the stress scenarios

We use balance sheet and income statement data as of Oct 30, 2018 to estimate the pre-shock probabilities of default. Thus, all our results in this section should be interpreted as the effect of the given shock if it were to instantaneously happen on November 1st, 2018. We present all our results in terms of the overall distribution pd from the 10th to the 90th percentile prior to and after the stress event.¹⁰

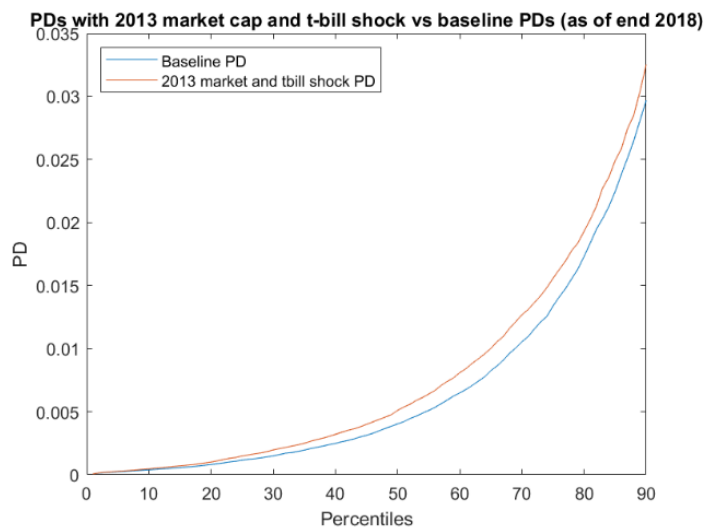
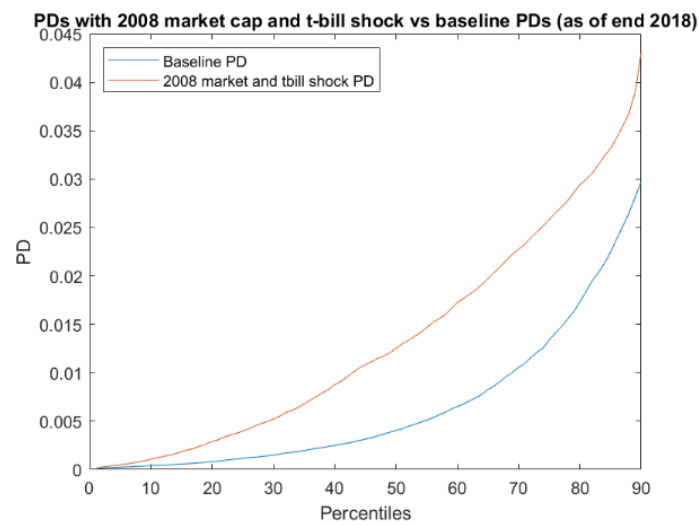
5.1 Actual Stress Scenarios

In figure 4, we present the results for the overall effect of the 2008 crisis and the 2013 crisis. Figure 4 shows that the severity of the crisis of

¹⁰ The reason for presenting from the 10th to the 90th percentile as opposed to the full percentile distribution is that the firms above the 90th percentile typically have a very high probability of default. The resulting graph scales close to 1 which implies that the differences for other sets of firms are not easily visible.

2008 impacted almost the entire distribution of credit risk with virtually the entire range from the 10th to the 90th percentile suffering large changes in credit risk. Even at the 50th percentile, the probability of default jumps from 0.25% to around 1%, a doubling in the risk of default. For the 90th percentile, the probability of default jumps from 2.5% to almost 6.5%, an increase of almost 2.5 times. Interestingly, there is a sharp non-linear effect of the 2008 crisis on firms beyond the 85th percentile, which is possibly due to the non-linear effect of increases in interest to EBITDA ratio.

Figure 4: Overall Impact of the 2008 and 2013 crisis (as of end 2018)



In contrast to the above, the taper tantrum resulted in much smaller increases in the credit risk of Indian firms. The median credit risk increases from 0.25% to 0.5%, which is half of the increase relative to the 2008 crisis. At the 90th percentile, pd increases to 4.5%, which is also much smaller than 6.5%, which was the value of the 90th percentile for the 2008 crisis. Finally, in contrast to the 2008 crisis, there is no sharp non-linearity in the increases in probability of default.

The above analysis can also be extended to examine the effect of each shock on industry level vulnerability. Using the industry classification described earlier, we present the change in the 20th percentile pd of the industry for the 2008 and 2013 shock in table 4.¹¹ First, the overall effect for the change in pd is 1.12% for the 2008 crisis whereas it is 0.22% for the 2013 crisis. Thus, the 2008 crisis had a more than a five-fold impact on the pd at the aggregate level.

Interestingly, the two shocks have quite different impact on the different industries. For the 2008 shock, the industry most impacted was cement. Other industries which had large increases in pd are agriculture, infrastructure, textiles and food production. For the 2013 shock, the industries most impacted is basic metals and metal products, infrastructure, agriculture and cement. Thus, while there is a large correlation among the industries that are impacted by the shock, there are still some significant differences in the actual pd increase which can be useful as a regulatory tool. In fact, if one were to view the 2008 crisis as roughly five times as severe as the 2013 crisis in terms of pd change, this ratio varies significantly across industries. For example, in the 2013 crisis, the retail industry only has an increase in pd of 0.09% versus 1.14% for the same industry in the 2008 crisis, which suggests a 12 fold difference, which varies hugely relative to the unconditional factor of 5. Similarly, the petroleum industry has a 0.20% increase in pd in the 2013 crisis while it has a 1.56% increase in pd in the 2008 crisis, which is a 7.8 times increase in the shock severity for the given sector.

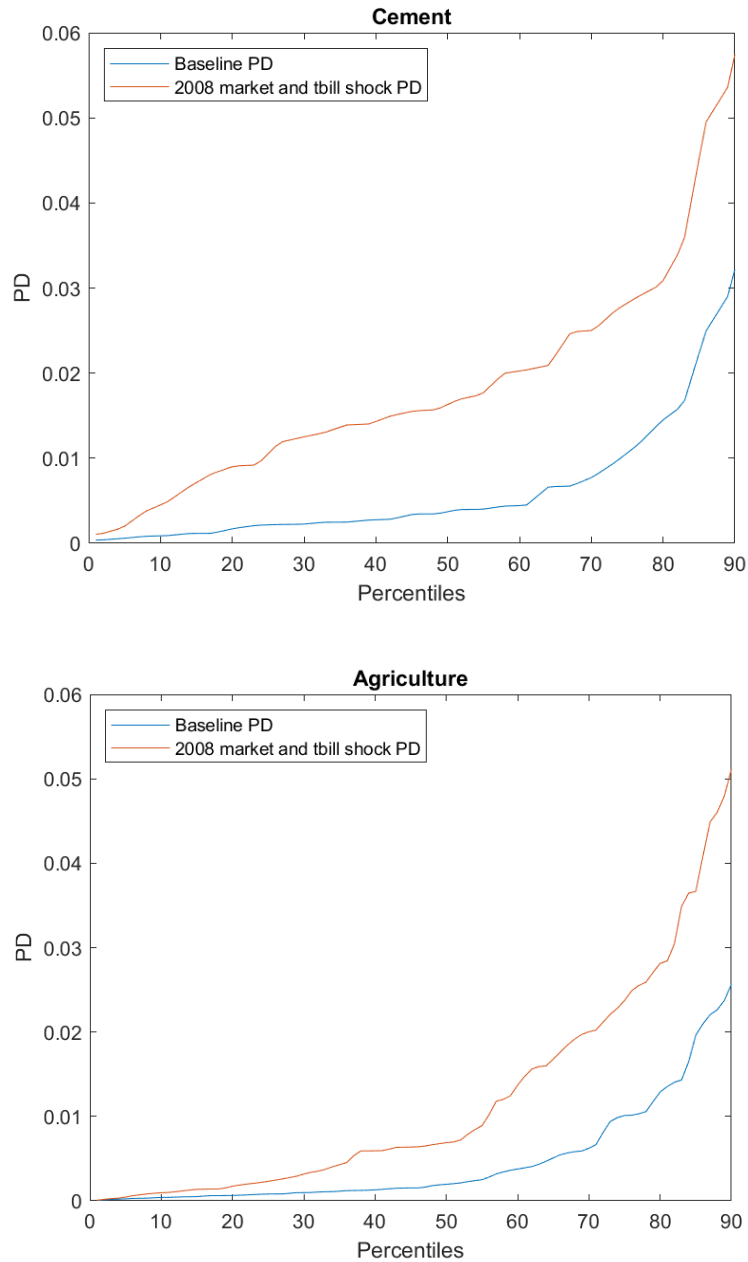
¹¹ We choose the 20th percentile as firms in the top 20 percent in terms of default probability are the one most likely to default in the short term or when a crisis hits. Thus, the increase in default probability of these firms is most interesting from a policy point of view. Although the median pd firm may also have a large increase in default probability, the total pd post crisis may be still be such that the firm is not very likely to default.

Table 4: Change in 20th percentile of pd by Industry for 2008 and 2013 Shock

RBI Industry	2008 Shock	2013 Shock
Agriculture	2.00%	0.43%
Basic Metal and Metal Products	1.63%	0.57%
Cement	2.17%	0.36%
Chemicals	1.56%	0.27%
Construction	1.07%	0.26%
Engineering	1.54%	0.34%
Food Processing	1.72%	0.29%
Gems and Jewellery	1.49%	0.14%
Infrastructure	1.79%	0.44%
Mining	0.90%	0.23%
Others	1.16%	0.22%
Paper	1.22%	0.33%
Petroleum	1.56%	0.20%
Retail-Others	1.14%	0.09%
Services	0.86%	0.15%
Textiles	1.79%	0.51%
Vehicles, Parts and Transport Equipments	1.61%	0.35%
Overall	1.12%	0.22%

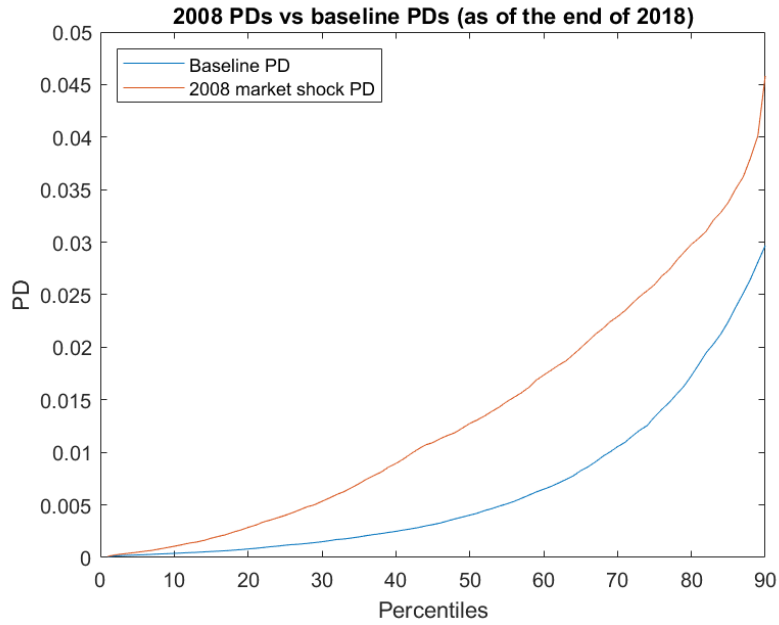
The average increase in credit risk across industries can be supplemented with the distributional impact of these shock across industries. When we compare the impact of the 2008 shock on the top 2 industries, we find that these vary significantly across these two industries. For cement, above the 80th percentile, there is an extremely large increase in pd suggesting a high likelihood of default. In contrast, below the 80th percentile, firms have a relatively parallel shift in their pd's. In contrast, for agriculture, the increase is broad based with a significant increase in pd from the 50th percentile onwards and a pattern where more ex-ante vulnerable firms have a higher increase in pd after the shock.

Figure 5: Overall Impact of the 2008 Shocks on Select Industries



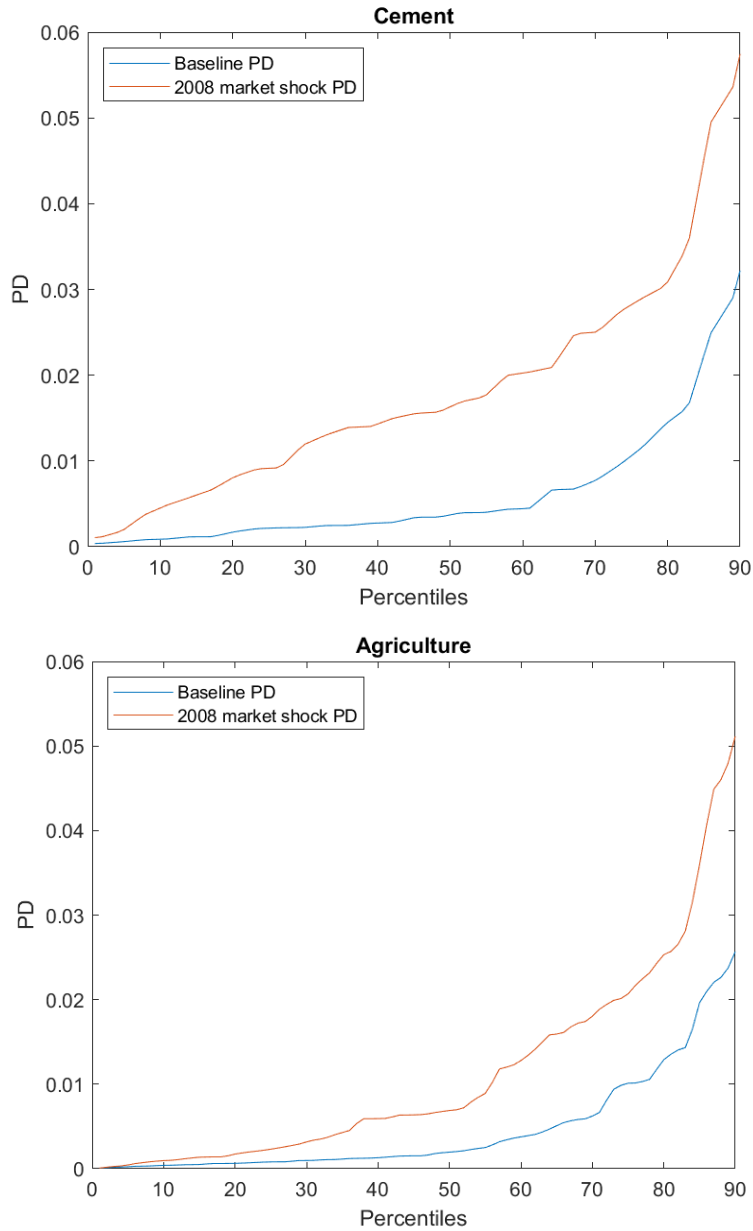
How much of the increase in probability of default is due to the market crash versus the increase in T bill rate? To estimate this, we replace the 2008 crash with one where the change in T bill rate is set to 0. We term this a 2008 market shock pd. The results are given in figure 6 and 7.

Figure 6: Overall Impact of the 2008 Market Shock



There is a large change due to market value alone, suggesting that increases in pd can result even in the absence of increases in financing costs due to increases in the treasury bill rates. A similar phenomenon is observed for the two industries affected most adversely during the 2008 crisis, as shown in figure 7.

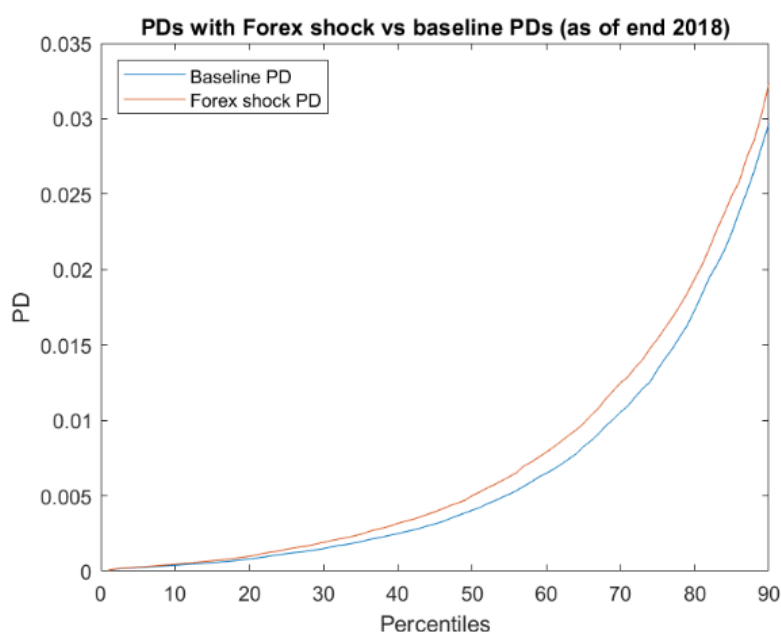
Figure 7: Impact of the 208 Market Shock on Select Industries



Another way our analysis can be used is to examine the effect of foreign exchange depreciations in the absence of any other effects, i.e., no other

market or financing effects.¹² There is a large literature in international finance that argues that quasi-fixed exchange rates encouraged borrowers to borrow in foreign exchange which created self fulfilling spirals with capital flight. While most foreign exchange crisis in a country are also accompanied by changes in the t bill rates, it is interesting to examine if the crisis primarily on account of increase in financing costs for the overall economy via the t bill effect, or due to a depreciation in foreign exchange rates, which may increases the costs of financing only for firms which have significant foreign currency debt outstanding. Figure 8 presents the results on the pd distribution for a 20% depreciation in the foreign exchange rate.

Figure 8: Impact of pure foreign exchange shock

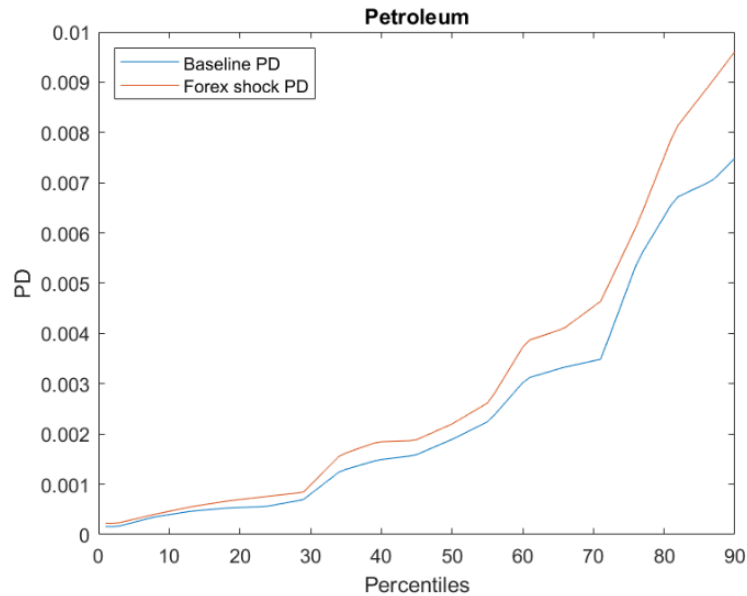


As can be clearly seen, a foreign exchange depreciation has miniscule effects on the probability of default without any increase in t bill rates, which would be the case if interest rate parity were to hold. Does this hold for all industries? We examine a few industries that are ex-ante more exposed to the foreign exchange rate. One important industry is the petroleum industry which is highly exposed to the US dollar exchange rate, since most contracts for oil are denominated in US dollars. Figure 9 presents the pd distribution for the petroleum industry. We do find large effects here, despite the fact that several

¹² Note that this is inconsistent with interest rate parity as a large foreign exchange depreciation would be necessarily accompanied by an interest rate increase.

firms in this industry are state-owned and therefore subject to an implicit sovereign guarantee.

Figure 9: Impact of foreign exchange shock on Petroleum industry



To summarize, we illustrate how our stress testing framework can examine the combined effect of shock as well as isolate the effect of individual shocks. One interesting conclusion from the above analysis of foreign exchange shocks is that it is not the depreciation per se that increases pd, but rather the increases in t bill rates that usually accompany a foreign exchange depreciation that result in an increase in pd.

6. Conclusion

We develop a model for developing stress tests for the economy to understand the behavior of probabilities of default during periods of macroeconomic and financial distress. Our model is amenable to predict combined effects of shocks in financing (measure by the treasury bill rate), markets, and the foreign exchange rate. The model only requires publicly available data and is easily implementable – thus can be implemented by regulators as well as financial institutions seeking to stress test their portfolios to various shocks. The model can provide industry level vulnerability indicators for various types of shocks as well.

From the stress tests conducted, we find steep non-linear effects of a of stress on firms at the highest pd deciles. From the various shock scenarios examined, we find that if shocks equaling those that occurred in 2008 were to occur in October 2018, the rise in both economy-wide and industry level vulnerability is the highest compared to other shock scenarios.

Although not the primary goal of this paper, we also develop a simple model for default prediction of publicly traded firms in India which has a high out-of-sample ROC (86%) and can lead credit rating agencies as an early warning system for default by publically listed firms by 2 quarters. The primary variables of interest in the model are book to market ratio (total assets divided by the sum of total assets and market capitalization), interest to EBDITA ratio, liquidity (cash and cash equivalents divided by total assets) and the model is robust to the inclusion of other controls. Furthermore, the model also provides a metric of industry level default.

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Appendix A

The following variables are used in the default prediction model:

i. Liquidity

An annual measure whose value is taken as of the beginning of the calendar year t for company i and is calculated as:

$$\text{Liquidity}_{i,t} = \frac{\text{Cash and Cash Equivalents}_{i,t}}{\text{Total Assets}_{i,t}}$$

If cash and cash equivalents are missing, they are set to 0.

ii. Interest Expense to EBIDTA

Interest Expense to EBIDTA (Int2PB) is an annual measure whose value is taken as of the beginning of the calendar year t for firm i and is calculated as:

$$\text{Interest Expense to EBIDTA}_{i,t} = \frac{\text{Interest Expense}_{i,t}}{\text{EBDITA}_{i,t}}$$

If the interest expense to EBIDTA ratio is negative, it is set to the value of the 99th percentile of the interest expense to EBIDTA ratio.

iii. Book-to- Market Ratio

Book-to- Market Ratio (Bk2Mkt _{i,d}) is a daily measure whose value is taken as of the beginning of the calendar year t for firm i – as follows:

$$\text{Book to Market Ratio}_{i,d} = \frac{\text{Book Value of Assets}_{i,t}}{\text{Market Capitalization of Equity}_{i,d} + \text{Book Value of Assets}_{i,t}}$$

iv. High Leverage Dummy

An annual measure whose value is taken as of the beginning of the calendar year t for firm i and is calculated as:

$$\text{Leverage}_{i,t} = \frac{\text{Total Debt}_{i,t}}{\text{Total Assets}_{i,t}}$$

If the value of $\text{Leverage}_{i,t}$ is greater than 0.8, $\text{High Leverage Dummy}_{i,t}$ is set to 1 else 0 i.e.

$$\text{High Leverage Dummy}_{i,t} = \begin{cases} 0 & \text{if } \text{Leverage}_{i,t} < 0.8 \\ 1 & \text{if } \text{Leverage}_{i,t} \geq 0.8 \end{cases}$$

v. Altman Z-score Dummy

The Altman Z-score calculates the likelihood of a publicly traded manufacturing company becoming bankrupt based on the company's profitability, liquidity, leverage, activity level and solvency (as detailed in Altman, 1968). For a firm i on day d , it is calculated as follows:

$$\begin{aligned} \text{Altman Z score}_{i,d} = & 1.2 \left(\frac{\text{Working Capital}_{i,t}}{\text{Total Assets}_{i,t}} \right) + 1.4 \left(\frac{\text{Retained Earnings}_{i,t}}{\text{Total Assets}_{i,t}} \right) + \\ & \left(\frac{\text{EBDITA}_{i,t}}{\text{Total Assets}_{i,t}} \right) \\ & + 0.6 \left(\frac{\text{Market Capitalization}_{i,d}}{\text{Total Assets}_{i,t}} \right) + 0.99 \left(\frac{\text{Total Sales}_{i,t}}{\text{Total Assets}_{i,t}} \right) \end{aligned}$$

When the Altman z-score is less than 1.8 for firm i , the likelihood of bankruptcy is high. Thus, we set the Altman z-score dummy ($azs_dum_{i,d}$) to 1 if $azs_{i,d} < 1.8$ and 0 otherwise, i.e.

$$\text{Altman Z - score Dummy}_{i,d} = \begin{cases} 0 & \text{if Altman Z score}_{i,d} \geq 1.8 \\ 1 & \text{if Altman Z score}_{i,d} < 1.8 \end{cases}$$

vi. Ohlson's O score

The database so constructed is used for computing Ohlson's O- Score. Ohlson's O- Score (Ohlson, 1980) for firm i in year t is calculated as follows:

$$\begin{aligned} \text{Ohlson's O score}_{i,t} = & -1.32 - 0.407 \ln \left(\frac{\text{Total Assets}_{i,t}}{\text{GNP}_t} \right) + 6.03 \left(\frac{\text{Total Liabilities}_{i,t}}{\text{Total Assets}_{i,t}} \right) \\ & - 1.43 \left(\frac{\text{Working Capital}_{i,t}}{\text{Total Assets}_{i,t}} \right) + 0.0757 \left(\frac{\text{Current Liabilities}_{i,t}}{\text{Current Assets}_{i,t}} \right) - 1.72(X) - 2.37 \left(\frac{\text{Net Income}_{i,t}}{\text{Total Assets}_{i,t}} \right) \\ & - 1.83 \left(\frac{\text{Funds from Operations}_{i,t}}{\text{Total Liabilities}_{i,t}} \right) + 0.285Y - 0.521 \left(\frac{\text{Net Income}_{i,t} - \text{Net Income}_{i,t-1}}{|\text{Net Income}_{i,t}| + |\text{Net Income}_{i,t-1}|} \right) \end{aligned}$$

Where,

$$X = 1 \text{ if Total Liabilities}_{i,t} > \text{Total Assets}_{i,t}, 0 \text{ otherwise}$$

$$Y = 1 \text{ if a net loss (i.e. negative net profit) in year } t - t \text{ and year } t - 2$$

If the O-Score is positive i.e. greater than 0, then the likelihood of default is higher. Thus, if Ohlson's O Score $_{i,t} > 0$, Ohlson's O-score dummy ($os_dum_{i,t}$) is set to 1 else 0 i.e.

$$\text{Ohlson's O - score dummy}_{i,t} = \begin{cases} 0 & \text{if Ohlson's O score}_{i,t} \leq 0 \\ 1 & \text{if Ohlson's O score}_{i,t} > 0 \end{cases}$$

