Changes in Distance-to-default as a timely indicator of changes in credit ratings

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Abstract

The timeliness of the credit rating of a firm has been frequently called into question, particularly over the previous decade. This paper examines if changes in credit ratings be updated on a more frequent basis than at the frequency of updates in the accounting data. The paper find that *changes* in high frequency market price based measure of distance to default, augmented with accounting measures along with other firm characteristics such as ownership structure, can provide more timely updates on the probability of credit ratings upgrades or downgrades.

Keywords: Credit ratings, Distance to default, Merton model, Event study
JEL Classification: G21, G24, G32

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1. Introduction

At a given point in time, a credit rating reflects the opinion of a rating agency about the creditworthiness of a debt issue by a firm. More generally, these ratings are used as an indicator of the financial well-being of the firm issuing the debt security. While the role of credit ratings has come under severe criticism all over the world,[2] they remain the most widely used indicator of the credibility of a firm to repay debt. Investors, portfolio managers, mutual funds and pension funds continue to base their investment decisions in debt securities based on these ratings. Banks use credit ratings as a key input in their lending decisions.

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[2] The Dodd-Frank Act stipulates that credit ratings not be used as a measure of credit quality in the risk assessment of financial firm portfolios, starting from 2011.

In the face of the lack of a clear alternative, regulators continue to rely on ratings to set regulatory guidelines on investments by a financial firm.

The main criticism about ratings is their slow reaction to the deteriorating financial conditions of the borrower. The most recent examples include the case of AIG and Lehman brothers which had investment grade rating until the minutes before their collapse. This problem is an old one: the same was the case of the ratings of Enron and WorldCom in early 2000. Simultaneously, market prices had reacted sharply and in a much more timely manner to news and information, in comparison to changes in the credit ratings.

Given the dependence of prudential risk measurement on the credit ratings, are there ways to measure changes in credit risk in a more timely manner? Can changes in the financial health of the borrower be incorporated faster into credit risk measures than merely the levels of the credit ratings, and if so, can these changes be used to predict the changes in ratings accurately?

This paper seeks to examine the above questions. More specifically, it seeks a real time measure that can incorporate the changing financial conditions of a firm faster than the rating agencies. The approach in the paper is to use the distance to default (DtD) measure based on the Merton (1974) framework which views equity as a call option on a firm's assets, which measures how many standard deviations is a firm away from the default point. The advantage of using this approach is that it is based on the equity prices of a firm that are updated on a much more regular and higher frequency than either the credit ratings themselves, or the accounting variables that are inputs into alternative traditional models of credit risk assessment. The paper tests if *changes in DtD can predict changes in credit ratings* so that firms that are mandated to base credit risk assessment and reporting on credit ratings have access to more timely credit risk updates.

Two approaches are used to test this hypothesis. The first approach uses an event study framework which evaluates the behavior of cumulative changes in DtD before and after credit ratings of firms are revised. This non-parametric approach is a useful test to whether there is lead information in the changes to the DtD measure about a downgrade or an upgrade in credit ratings of firms. The second approach is parametric where a probit model is estimated with a rating downgrade as the dependent variable on changes in DtD as the predictive variable. This approach permits the flexibility of combining the changes in DtD with other traditional accounting ratios and financial variables to improve the explanatory and predictive power of the model.

The empirical analysis is conducted on a set of 1214 listed firms in India observed over a long period of time from Jul 1998 to Jan 2012. During this period, there were about 4710 rating revisions, out of which 4286 were reaffirmations, 245 downgrades and 179 upgrades.

The event study analysis shows that there is a significant and positive change in the DtD before a credit rating upgrade. In contrast, there is a significant decrease in the DtD prior to a credit rating downgrade. This is particularly strong for the period of around 40 days prior to the change indicating that changes in DtD does captures some information about the deteriorating health of the firm prior to the actions taken by the rating agency.

The results from the probit model strengthen these non-parametric insights. At all horizons, the coefficient associated with changes in DtD turns out to be significant. The model has an average accuracy ratio of 60%. In line with Campbell et al. (2008), the addition of the market and accounting based measures such as firm size, leverage ratio, income, liquidity ratio significantly improve the explanatory and predictive power of the model. A new variable that has been introduced in the model is the category of ownership by the government. This is particularly relevant for emerging markets where there tends to be a significant number of firms where the government has a large shareholding. The accuracy ratio of the model combining both the market price based DtD and these traditional accounting ratios and financial information comes upto 88%.

The paper contributes to the literature in the following way: most of the literature has looked at the ability of the market and accounting based measures to forecast financial health measured as the probability of default over a fixed period or a credit rating over that period. This paper provides new evidence on the ability of changes in these market price based DtD measures to predict changes in credit ratings for a firm. The paper provides evidence from both non-parametric as well as parametric probit model based approaches that the changes in the market price measures can help predict changes in credit ratings. Further, the results of the probit model indicate that large drops in the DtD over a 40-day period leads to a strong probability that the credit rating will be downgraded.

The remainder of this paper is organised as follows. Section 2 presents the alternative approaches and how well these models perform. The methodology of the event study and the probit model estimation is presented in Section 3. A description of the sample used in the paper is in Section 4 while Section 5 presents the results of both the event study and the probit analysis. Section 6 concludes.

2. The toolkit of credit risk models

Over the last several decades, there has been a lot of research that is carried out to model the credit risk of a firm. The output of these models can vary from the probability of default of a firm on a payment due over a fixed time horizon to a credit ranking or a rating as the desired output, although most focus on the probability of default. There are two clearly defined approaches that creates a distinct dichotomy in the empirical models: the set of statistical models that are based on the empirical characterisation of firms that default in relation to firms that do not, and the more structural models that are developed from the use of a theoretical model.

The first set of models use information from the balance sheet and other financial reports issued by firms on a regular basis to create accounting ratios to measure the likelihood of bankruptcy (Altman, 1968; Ohlson, 1980; Zmijewski, 1984). While these models have been extremely popular (Altman and Katz, 1976; Kaplan and Urwitz, 1979; Blume et al., 1998), they are criticised on the following:

1. The absence of an underlying theoretical model.
2. Timeliness of information: These models use financial statements information which are based on past performance and are available only at either a quarterly or annual frequency. These models thus fail to capture changes in the financial conditions of the borrowing firm.
3. The methodological criticism that these models are single period models, with biased and inconsistent estimates based on the specific sample used (Shumway, 2001; Chava and Jarrow, 2004).

These criticisms gave rise to a second type of probability of default models with a more structural basis. The best known of these is likely Merton (1974) which models equity as a call option on the firm's underlying assets under the assumption of limited liability, and which proposed using information about the equity and debt of the firm to first estimate the value of the firm, and then how close the firm is to default. In addition to the theoretical underpinning of the option pricing model, the model also has the advantage of taking high frequency information inputs such as market prices of equity and debt. Since market equity prices are more frequently available than market bond prices, ensuring research operationalised the Merton (1974) model by using equity prices to measure financial health (Vasicek, 1984; Crosbie and Bohn, 2003). Crosbie and Bohn (2003) propose the "distance to default" (DtD) which measures how many standard deviations a firm is from default.[3]

Several papers investigate whether the level of the DtD is a useful indicator of the probability of default of a firm. Oderda et al. (2003), Kealhofer (2003) and Vassalou and Yuhang (2004) find that DtD performs much better as a measure of bankruptcy compared to the rating agencies. Gropp et al. (2006) analyses the ability of the equity based DtD and bond spreads to signal fragility of European banks, and find that DtD can accurately capture the probability of a rating downgrade (to C or below) of a bank 6 to 18 months in advance of the downgrade itself.

However, even these models have their disadvantages. Unlike the accounting variables which are observed for all registered firms, the DtD can only be measured for firms that are listed and traded on public exchanges. The quality of

[3] The DtD formula to be put in the text.

the DtD measure thus depends upon the quality of the prices themselves, which in turn depends upon the liquidity of the market for the shares.

Several papers carry out a comparative analysis of the models using accounting and market based measures. These present mixed results on how much more power the DtD has over the information in the accounting data, to measure the probability of firm default. Hillegeist et al. (2004) and Agarwal and Taffler (2008) find that there is considerable improvement in the quality of the DtD forecasts when the DtD measure is used in conjunction with the traditional accounting variables. More recently, Campbell et al. (2008) and Bharath and Shumway (2008) show that the DtD measure has relatively little explanatory power over these accounting variables. Campbell et al. (2008) and Campbell et al. (2011) identify an additional set of financial measures such as price levels, volatility of returns, equity to book ratio and profitability that when directly used instead of the DtD measure, enhances the power of the traditional statistical models to capture the probability of firm default.

Most of these studies concentrate on the use of market data and accounting based measures to capture the probability the firm will default over the coming year. Few have investigated whether *changes* in these measures, particularly those based on higher frequency market data, can be useful to predict changes in the financial condition of the firm. This paper focusses on testing the proposition of whether the explanatory power of these accounting and market based models have any predictive power in predicting credit rating changes.

Inherent in this question is the assumption that rating changes capture the changing credit quality of the firm. Despite the criticisms about credit ratings, we use them as the benchmark for changing credit quality as these ratings are typically the only directly observed, publicly available measure of credit risk of a firm that is consistently available across all markets. Ratings are especially important as an indicator of financial health in emerging markets which have weak legal and enforcement framework for bankruptcy. Credit ratings have become the mainstay of credit risk evaluation by financial firms that engage in asset management or lending firms such as banks. The importance of credit ratings has become entrenched over the several decades in the past, when financial sector regulators have based risk measurement rules and guidelines for asset managers largely on credit ratings. It is over the last two decades that credit ratings have been observed to fall sharply short of playing their role: they have clearly failed in providing timely information of the financial health of the firm, lagging behind other measures such as stock market prices of listed securities of firms.

On one hand, credit rating agencies have been slow to adopt the real-time measures of market prices into their credit risk models. On the other hand, the failure of credit ratings to be timely indicators could merely be a reflection of their policies on how ratings are updated. Credit rating agencies are paid for the rating of debt securities when they are first issued. Beyond this, their continued role is in updating these ratings is often not. Certainly, in emerging market economies, rating updates are done less systematically, and are typically updated only immediately prior to a credit event (such as a bankruptcy or a well-defined corporate action like a merger or acquisition). Since the ratings are a critical input to prudential rules on fund management, unexpected and infrequent changes have a discontinuous impact of the quality of funds and the performance of fund managers in such economies. Thus, even though credit ratings themselves have such low credibility to capture the financial health of the firm, changes in the ratings are widely accepted as a credit event.

In this paper, we draw upon the belief focusses on whether changes in the DtD over a given interval of time can predict a rating change. The motivation to examine this is because ascertain the DtD measure which can be updated at higher frequencies than the credit rating, can be used to manage credit risk in portfolios of large fund management companies, which have regulatory constraints on the credit quality they can hold. This is especially useful considering that the alternative of accounting data gets updated on an annual, or at best a quarterly, basis in such countries. In the next section we discuss our methodology and the issues involved in detail.

3. Methodology

Both the approaches of the event study and probit model estimation are well-established in the literature. The expected behaviour of the distribution of DtD or changes in DtD is however not well understood. This is unlike in the case of returns, for which there are well-established priors about the expected distribution and time series behaviour. There are neither well accepted empirical characterisations, nor established theoretical basis, about the kind of distribution that the estimated values the DtD of a given firm should have. Thus, any modelling involving the empirical behaviour of changes in DtD will involve an effort to establish what the expected behaviour of the DtD should be.

3.1. Event study analysis

Traditionally, event studies have been used to study the impact of corporate announcements on equity returns. For a set of firms that undergo a fixed type of corporate action/announcement, the return is calculated each day, and then cumulated daily until the date of the event. In the case of returns, the cumulative abnormal returns (CAR) over a fixed event window are compared before and after the event under the null of no impact of the announcement. We adopt the same framework to determine if the credit rating changes are predicted by the changes in DtD.

The event ($t = 0$) is defined as the day of announcement of credit rating change. The event window is taken as 120 days. For each firm in the sample that is downgraded, upgraded or reaffirmed, we calculate the cumulative change in DtD (cDtD) over the length of window before t = 0 and after t = 0 as:

$$\text{cDtD}_{t<0} = \Sigma_{t=-N}^{-1} \Delta\text{TDD}$$

$$\text{cDtD}_{t>0} = \Sigma_{t=1}^{N} \Delta\text{DtD}$$

The event analysis is conducted separately for downgrades, upgrades and reaffirmations, to understand by how much the cumulated change in DtD occurs before, and after, the credit rating change. A significant drop (rise) in DtD *before* a rating downgrade (upgrade) will imply that the changes in the DtD reflect the deterioration in firm's health prior to the credit rating agency, and that the DtD change can predict credit rating changes. On the other hand, a change in DtD in the direction of the event *after* a rating change will suggest that DtD changes lag the credit rating changes.

We use a bootstrap procedure to draw the inference for the event study. The advantage of bootstrap inference is that it is free from the distributional assumptions for the DtD or changes in DtD, such as normality, which is made in case of the standard t-test. We draw the bootstrap 95% confidence intervals for each type of credit rating change in order to test whether cDtD is significantly different from zero at any interval.

3.2. Probit model analysis

We also estimate a probit model to infer if changes in DtD at different intervals can predict a rating change. We first consider a simple specification involving only changes in DtD as the explanatory variable over different time horizons. The model can be given as:

$$Pr(Y_i = 1) = \phi(\beta_0 + \beta_1 \text{cD}\textsc{t}\text{D}_{i,-N})$$

where

$$Y_i = \begin{cases} 1 & \text{if Rating downgrade} \\ 0 & \text{otherwise} \end{cases}$$

In the above model our primary focus is on rating downgrades, and whether these can be predicted by a DtD change. Therefore, Y_i is defined as 1 if there is a rating downgrade for the bonds of firm i and 0 if there is a rating upgrade or reaffirmation. ϕ represents the cumulative normal distribution. $\text{cDtD}_{i,-N}$ represents the change in DtD N days prior to the rating change date. Thus, $\text{cDtD}_{i,-1M}$ implies change in DtD of firm i over a one-month period prior to the day of rating change. We use monthly data to estimate the model at four different values of N, where $N = 1$ month, 3 months, 6 months and 12 months prior the day of rating change day.

Further, we test which interval has the most impact on predicting changes in credit ratings by using the following specification:

$$\begin{aligned} Pr(Y_i = 1) &= \phi(\beta_0 + \beta_1 \text{cDtD}_{i,-1M} + \beta_2 \text{cDtD}_{i,-(3M-1M)} \\ &\quad + \beta_3 \text{cDtD}_{i,-(6M-3M)} + \beta_4 \text{cDtD}_{i,-(12M-6M)}) \end{aligned}$$

$\text{cDtD}_{i,-(3M-1M)}$ represents the change in DtD between the three month period prior the rating change and one month prior the rating change. This implies the change in DtD over a two month period, one month before the rating change. The rationale for this specification is to include changes in DtD over an entire one year horizon as a continuous set of changes in DtD variables over non-overlapping periods. This will help to determine the horizon at which changes in DtD predict the changes in rating best.

A more careful understanding of the DtD measure shows that these will be significantly influenced by the leverage and the volatility of the firm. This will have implications on how we use the changes in DtD in the model specification. This analysis is presented in the following section.

3.2.1. Sensitivity of DtD to equity prices, volatility and leverage

The three key inputs used in calculating the DtD for a firm are market capitalisation, debt, and the volatility of equity. This implies that the DtD is influenced by the leverage – ratio of debt to the sum of equity and debt – and volatility of the firm. A higher value of DtD can be obtained either because the leverage of the firm is high or because the volatility is high or both.

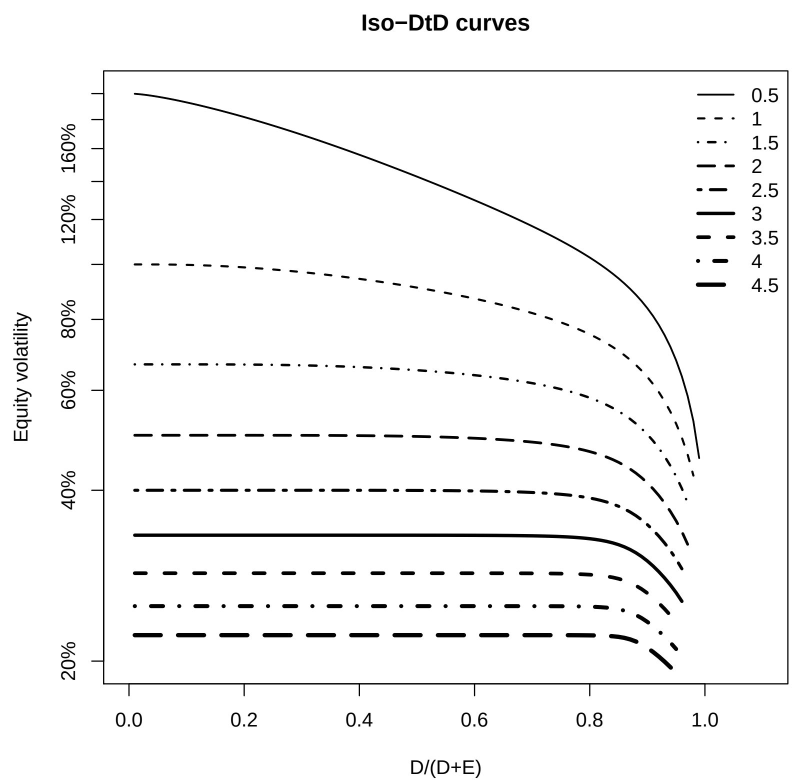
In this section, we evaluate the sensitivity of DtD to each of these inputs by drawing ISO-DTD curves, across varying levels of leverage and equity volatility.

We plot ISO-DTD curves for nine different values of DtD in Figure 1. The graph shows that at a fixed level of volatility and low levels of leverage, DtD changes are small and insignificant for changes in leverage. DtD changes (drops towards zero) significantly only for much higher levels of leverage (beyond 80 percent). For a constant level of leverage, DtD shows significant drops for changes in equity volatility. This implies that more than leverage, it is equity volatility that has a greater influence in driving large changes in DtD.

This has some implications for interpreting and using the market based DtD as a measure of credit quality. When overall market volatility is high, it is likely that even small changes in the leverage will cause large changes in the DtD. Thus, during episodes such as the financial crisis of 2008, when systemic volatility reached peak levels, the market reacted much more strongly to even small changes in leverage. During the cal, periods, these same changes in leverage would have generated much smaller decreases in DtDs. Thus, the interpretation of changes in DtDs have different implications on changes in firm credit

Figure 1 ISO-DTD curves

The figure shows simulated ISO-DTD curves for nine different values of DtD with respect to leverage and equity volatility. One can clearly see that DtD is much more sensitive to equity volatility than the leverage even at low levels.



quality during periods of high and low volatility. This implies that the information in the DtD changes is conditioned on the level of volatility and the leverage of the firm. For this reason, we include the values of leverage and volatility in our probit model estimation.

3.2.2. Implications for the probit model specification

Based on the discussion in the previous section, we include leverage and volatility as additional variables in our model. These variables are defined as follows:

1. Leverage ($\text{LEVER}_{i,t}$): measured as the ratio of total debt of the firm to the sum of debt and equity (measured by market capitalisation),
2. Volatility ($\text{VOL}_{i,t}$): measured as the historical volatility in the equity prices of the firm over the past 1 year.

Besides, we also use other accounting variables that are expected to play an important role in determining the financial health of the firm and have also been used in previous studies (Campbell et al., 2008, 2011). These variables include

3. Firm size ($\text{FSIZE}_{i,t}$): measured as the ratio of market cap of the firm i to the ratio of sum of market cap of all the firms in the sample at time t,
4. Profitability ratio ($\text{NIMTA}_{i,t}$): measured as the ratio of net income after taxes to market value of total assets (which is calculated as sum of book value of firm's debt and market value of equity).
5. Liquidity ratio ($\text{CASHMTA}_{i,t}$): measured as ratio of cash holdings to market value of total assets.
6. Excess returns ($\text{EXRET}_{i,t}$): measured as the difference between stock's return relative to a benchmark market index return. We use the S&P CNX Nifty as our benchmark index.
7. Prices ($\text{PRICES}_{i,t}$): we add the log stock price of the firm in our analysis. As noted in Campbell et al. (2011), distressed firms are expected to have lower prices.

We include the lagged values of all these variables, one month prior the rating change. The accounting variables are based on the annual data of firm accounting statements and are updated each year in July. Firm characteristics are added to the univariate as well as the multivariate model. The full multivariate model, including firm characteristics, is specified as:

$$\begin{aligned} Pr(Y_i = 1) \quad = \quad & \phi(\beta_0 + \beta_1 \text{CDTD}_{i,-1M} + \beta_2 \text{CDTD}_{i,-(3M-1M)} \\ & + \beta_3 \text{CDTD}_{i,-(6M-3M)} + \beta_4 \text{CDTD}_{i,-(12M-6M)} \\ & + \text{FSIZE}_{i,(-1M)} + \text{VOL}_{i,(-1M)} + \text{LEVER}_{i,(-1M)}) \\ & + \text{NIMTA}_{i,(-1M)} + \text{CASHMTA}_{i,(-1M)} + \text{EXRET}_{i,(-1M)} \\ & + \text{PRICES}_{i,(-1M)} \end{aligned}$$

We estimate the above set of models at monthly frequency. The monthly estimates for all the variables is derived by taking the average of the variable during that month.

In addition to the above characteristics, we also test if the ownership structure of the firm impacts the probability of a rating downgrade. We test this by introducing a dummy in our model, DGOVT which takes value 1, if the firm is a government owned firm and zero if it is held privately. We expect that a government owned firm has less chances of a downgrade vis-a-vis a privately held firm since a government owned firm has greater chances of getting a capital infusion from the government. We also test for industry effects, primarily, by adding a dummy DFIN which takes value 1 if a firm is a financial services firm (which includes banks and all other firms which are involved in the business of financial services like insurance, housing loan agencies etc) and zero if it is a manufacturing firm. The likelihood of a financial services firm to get a bailout is more likely than a manufacturing firm as it poses systemic risk in the system.

So we expect a negative relation between the probability of a downgrade and the dummy DFIN.

Finally, in order to determine if the values of DtD change do have any explanatory power in determining the probability of a downgrade, we also estimate another model with just the firm characteristics.

3.2.3. Model validation

We compare how well the model fits across alternative specifications using two measures:

- The first of these is the *McFadden pseudo-R^2* which captures the performance of the model vis-a-vis a model that only fits the overall average default rate (captured by the intercept term). We also report the *Adjusted McFadden pseudo-R^2* which penalizes for the number of explanatory terms in the model and increases if the new term improves the model.
- The second is the *accuracy ratio* (ACR) which compares the number of correct predictions of a probability of default (of downgrade in the present case) from the model to the number of incorrect predictions.

4. Data

The analysis is done on a broad set of firms that are listed on Indian equity markets, that are part of the COSPI[4] index published by CMIE[5]. The COSPI index set includes all those firms that have a trading frequency of at least 66 percent of the days in the six months prior to a given date. For the analysis in this paper, the latest available set of COSPI firms are extracted from the database. Out of these, those firms which have more than 30 days of missing price data consecutively are filtered out. The final number of firms in the sample is 1214.

The period of analysis is from Jan 1998 to Jan 2012. We obtain the data on credit rating changes, prices, financial an accounting variables from the Prowess database published by CMIE. Table 1 presents the summary statistics on the market based DtD measure including market capitalisation, leverage and equity volatility used in DtD calculation.

4.1. Distance-to-Default (DtD) estimation

For each firm in the sample, we calculate a daily time series of the DtD for the firm. The data used in these estimations is as follows:

[4]COSPI is the CMIE Overall Share Price Index.
[5]Centre for Monitoring Indian Economy

Table 1 Summary statistics

The table reports the summary statistics for the Distance-to-Default (DTD) of the firms as well as the other key measures that are the traditional inputs into evaluating the financial health of a firm. LEVER is the Leverage, VOL is Volatility, FSIZE is the market cap of the firm by total market cap of the sample, NIMTA is the Profitability ratio, CASHMTA is the Liquidity ratio, EXRET is the Excess returns and PRICES is the Log(Market price) for the firm.

	DTD	LEVER	VOL	FSIZE	NIMTA	CASHMTA	EXRET	PRICES
Min	1.155	0.1192	0.4090	0.0825	-0.0078	0.0004	-0.1092	3.132
Q1	1.437	0.1878	0.4541	0.0989	-0.0008	0.0007	-0.0063	3.690
Median	1.775	0.2467	0.5251	0.1592	0.0052	0.0012	0.0000	4.002
Mean	1.790	0.2440	0.5682	0.1474	0.0044	0.0012	-0.0005	4.035
Q3	2.156	0.3016	0.6762	0.1822	0.0078	0.0016	0.0056	4.413
Max	3.077	0.3688	0.8126	0.2294	0.0249	0.0021	0.0755	5.026
S.D.	0.384	0.06	0.1248	0.0425	0.0062	0.0005	0.0105	0.4098

1. Market capitalisation (V_E): It is calculated as the product of the closing price of the firm equity as traded at the *National Stock Exchange of India* (NSE) and the shares outstanding.[6]
2. Equity volatililty (σ_E): This is calculated as the standard deviation of returns over the past 250 days.
3. Risk-free interest rate (r_f): This is calculated from the one-year Government of India treasury bill prices.[7]
4. Threshold debt level (X): The value of the threshold debt level for the firm is defined as equal to the short-term liabilities and half of the long-term liabilities, similar to the definition used by the KMV model. The data is available at annual frequency. For the purpose of the analysis, we assume that the liabilities for the firm remains the same for the financial year.[8]
5. Time: Maturity of one year.

Figure 2 plots the weighted average values of the four market based measures for the firm used in this analysis: market capitalsation ratio, volatility, leverage and DtD.

We see a sharp fall in the value of distance to default during the 2008 financial crisis period. In addition, we also observe a one to one inverse relation between average DtD and average volatility. This is consistent with the discussion in Section 3.2.1 which showed DtD is highly sensitive to volatility.

Table 2 Credit events listed by year

The table lists the total number of firms that were downgraded, upgrades and reaffirmed for each year separately.

	1997	1998	1999	2000	2001	2002	2003	2004	2005
Downgraded	0	5	6	4	2	5	1	0	0
Reaffirmed	25	82	94	121	166	172	169	122	174
Upgraded	0	0	0	1	3	1	1	3	0
	2006	2007	2008	2009	2010	2011	2012		Total
Downgraded	0	1	4	15	24	153	25		245
Reaffirmed	210	226	235	556	806	1037	91		4286
Upgraded	1	0	0	3	46	112	8		179

4.2. Credit events

The available ratings data contains the final rating and all the rating change on debt instruments. Table 2 presents the rating changes for the firms in the sample. There are about 4710 rating revisions, with the majority of them being reaffirmations. A striking feature is that the majority of the upgrades and downgrades were announced in the period after the 2008 financial crisis.

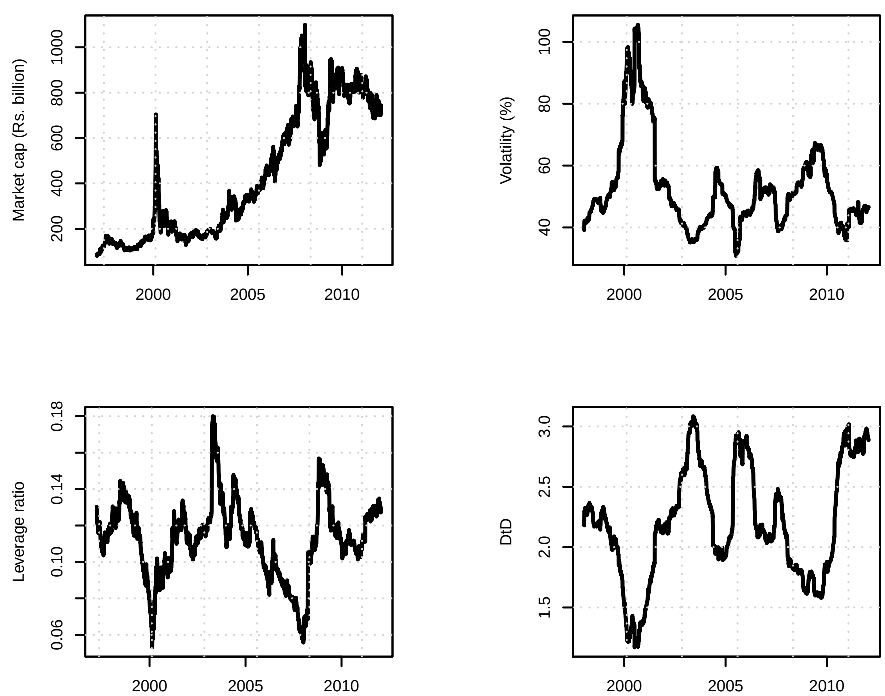
[6] These were extracted from the Prowess database on firms, published by the *Center for Monitoring Indian Economy* (CMIE).

[7] The data is available from the *Fixed Income Money Market and Derivatives Association* (FIMMDA) website. `http://www.fimmda.org`

[8] In India, the financial year spans from 1^{st} April to 30^{th} March of the following year. Since the results by the firms are announced during May and June, we update these variables in July each year.

Figure 2 Time series of market-based firm characteristics

The four graphs show the weighted average of the four market based measures used in the analysis: market capitalisation, equity volatility, leverage and Distance-to-Default (DtD). These have been calculated over a sample of 1214 firms during the period from 1997 to 2012. Equity volatility is the historical variance of returns over the past 250 days. Leverage is computed as the ratio of debt to market capitalisation.
All the averages are computed based on daily market capitalization weights of the sample firms.



5. Results

The results of the non-parametric event study is presented first, that helps to identify whether changes in DtD do contain information about forthcoming changes in credit ratings. Next, a parametric approach using a probit model to fit the probability of a rating downgrade is carried out.

Figure 3 Average change in DtD 120 days before and after a rating change

The graphs shows the average cumulative change in DtD for the sample firms that undergo an upgrade, re-affirmation or a downgrade during the sample period.
The dotted line in each graph shows the 95% bootstrap confidence intervals. The wider confidence bands in the downgrades graph indicate that changes in the value of the DtD around a rating downgrade varies widely in the sample.

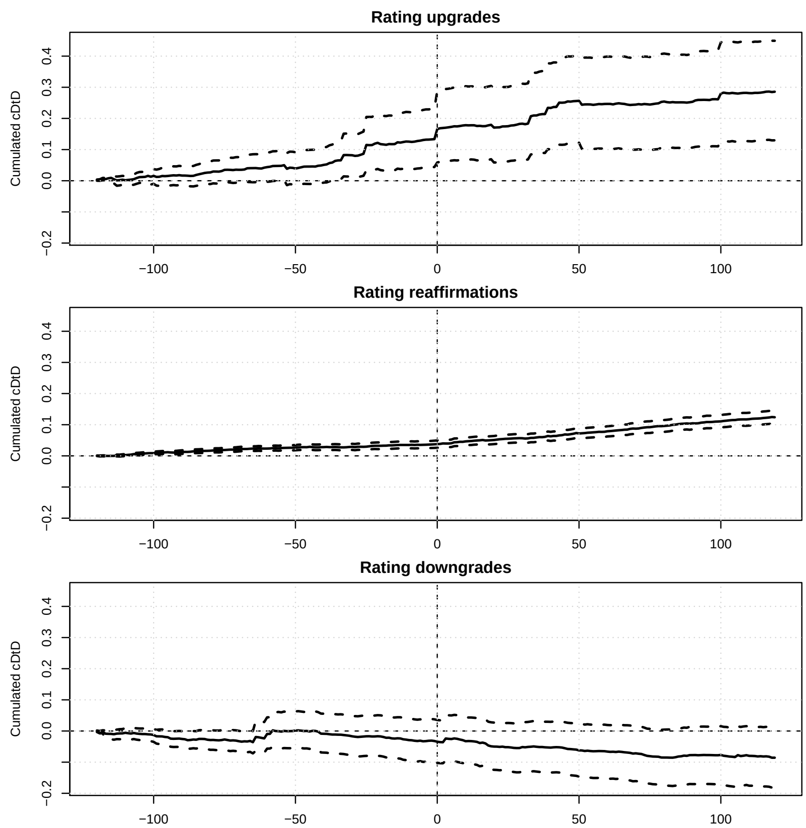


Figure 3 plots the cumulative changes in DtD (cDtD) along with the 95% bootstrap confidence intervals, for the sample of firms whose ratings are downgraded, upgraded or reaffirmed. The event window is defined as 120 days before and after the rating change announcement.

The first panel shows the average cumulative cDtD for the firms that had ratings *upgrades*. There is a significant increase in DtD around rating upgrades, both before and after the credit rating change. The rate of increase in DtD after the change is announced is lower than the rate prior, which indicates that changes in the DtD captures the financial health information before the rating announcement.

The third panel shows the cumulative cDtD for the firms that underwent a ratings *downgrade*, where it shows a fall 40 days prior the credit rating downgrade. This suggests that changes in the DtD can be used to measure the deterioration in a firm's health approximately one month prior to the rating agency's assessment.

5.2. Probit analysis

The probit model is estimated to test whether a change in DtD over a defined time period can be a factor determining the probability of a credit rating downgrade. This is done in two broad steps:

1. Estimate a probit model and test for the link between the probability of a credit rating downgrade with changes in the daily DtD over different time periods.
   This is done in order to identify the time horizon over which the cDtD is most informative about possible changes in the credit rating.
2. Once the time horizon has been located, estimate a probit model that incorporate both the cDtD as well as the accounting ratios and other financial variables for the firm.
   This is done to improve the performance of the model determining the probability of a credit rating downgrade.

Table 3 reports estimates for the probit model, where the output is the probability of a rating downgrade for a given firm, and the input is the cDtD over varying time horizons. Among these four models, Model 3 has the highest accuracy ratio of 62%.

The coefficients associated with cDtD over all horizons are negative, which is consistent with the expected inverse relationship between changes in DtD and ratings. When DtD decreases (goes closer to zero), it implies that the credit quality of the firm has worsened which, in turn, implies an increase in the probability of a downgrade. However, only the coefficients for cDtD over 1 month and 3 months are significant. Thus, cDtD over the most recent period matters far more to explain the probability of a rating downgrade, than the cumulative cDtD over longer time periods. This implies that the market gets a sense of a firm's creditworthiness deterioration at month before the rating agency.[9] In the models that follow, instead of the overlapping cDtD variables used in Models $1-4$, we shift to using a set of cDtD variables where the changes are calculated

[9]Gropp et al. (2006) find similar results. They use levels DtD data to determine if DtD can predict downgrades. However they find that at the intervals of three months, the coefficients are insignificant. They attributed the reason to be increased noise in the months closer to the default/downgrades.

Table 3 Probit results of downgrades in credit ratings based on changes in DtD over varying horizons

The table reports the probit results for DtD changes over horizons over 1 month, 3 months, 6 months and 12 months. The values in parentheses are standard errors. Boldface values indicate significance at $p < 0.05$

	Model 1	Model 2	Model 3	Model 4
Intercept	**-1.72**	**-1.72**	**-1.71**	**-1.71**
	(0.04)	(0.04)	(0.04)	(0.04)
cDtD_{-1M}	**-0.42**			
	(0.17)			
cDtD_{-3M}		**-0.19**		
		(0.08)		
cDtD_{-6M}			**-0.16**	
			(0.06)	
cDtD_{-12M}				**-0.09**
				(0.04)
log L	-477.80	-478.10	-476.97	-478.38
pseudo-R^2	0.01	0.01	0.01	0.00
Adjusted pseudo-R^2	0.00	0.01	0.01	0.00
ACR	0.60	0.60	0.62	0.58

Standard errors in parentheses

over non-overlapping horizons. For instance, cDtD_{3M-1M} indicates the difference in the DtD from three months and the DtD from one month, prior to the date of the credit rating change.

The next four models estimated have both cDtD over the four different non-overlapping horizons covering one year from the date of the credit rating downgrade combined with other market based and accounting based variables introduced in Section 3.2.2. The probit regression results for these (Models $5-8$) are presented in Table 4. In this specification, each independent variable is recorded in previous month just prior the rating change.

Not surprisingly, the addition of the accounting and market based measures add significantly to the explanatory power of the model. Both the pseudo-R^2 and the adjusted pseudo-R^2 increase significantly to 19% (and 17%) from 1% value reported in Table 3. The accuracy ratio is 84% for each of these models. Out of the 4 models, Model 8 turns out to be the best which represents the DtD changes over one full year before a credit rating change.

The signs on the cDtD over all horizons are negative which is consistent with the hypothesis about the information of deteriorating financial health measured by negative values of cDtD. When the DtD falls, it implies an increase in the probability of downgrade of a firm. However, not all the changes are significant to explaining the probability of a downgrade. When used on it's own, the cDtD over short horizons are significant. But in conjunction with accounting ratios,

Table 4 Probit using non-overlapping DtD changes over the previous year

The models presented here include four variables for the changes in DtD from the date of the rating change to one year out. Model 5 uses cDtD over non-overlapping intervals. Model 6 has cDtD as well as the other market and accounting based measures used in Campbell et al. (2011). Model 7 has cDtD with dummy variables on Govt. ownership and whether the firm is a financial firm or not. Model 8 contains all the variables used in Models $5-7$.
The values in parentheses are standard errors. Boldface values indicate coefficient estimates that are significant at $p < 0.05$.
Model performance is measured by the log likelihood ($\log L$), the Pseudo-R^2 measures and the Accuracy Ratio (ACR).

	Model 5	Model 6	Model 7	Model 8
Intercept	**-1.71**	**0.88**	**-1.59**	0.50
	(0.04)	(0.37)	(0.05)	(0.41)
cDtD$_{-1M}$	**-0.40**	-0.32	**-0.46**	-0.41
	(0.18)	(0.26)	(0.19)	(0.25)
cDtD$_{-(3M-1M)}$	-0.09	**-0.43**	-0.11	-0.09
	(0.11)	(0.17)	(0.11)	(0.16)
cDtD$_{-(6M-3M)}$	-0.15	**-0.31**	-0.17	**-0.32**
	(0.09)	(0.14)	(0.10)	(0.15)
cDtD$_{-(12M-6M)}$	-0.02	**-0.20**	-0.03	**-0.21**
	(0.06)	(0.10)	(0.06)	(0.10)
FSIZE$_{-1M}$		**-4.01**		**-2.62**
		(1.11)		(1.16)
LEVER$_{-1M}$		**0.70**		**1.93**
		(0.29)		(0.37)
VOL$_{-1M}$		**-1.09**		**-1.12**
		(0.27)		(0.30)
PRICES$_{-1M}$		**-1.27**		**-1.13**
		(0.19)		(0.20)
NIMTA$_{-1M}$		-4.63		-3.92
		(3.23)		(3.21)
CASHMTA$_{-1M}$		**-0.01**		**-0.01**
		(0.01)		(0.01)
DGOVT			**-0.75**	-0.25
			(0.26)	(0.35)
DFIN			**-0.95**	**-1.71**
			(0.26)	(0.38)
log L	-467.03	-352.84	-438.74	-324.02
Pseudo-R^2	0.01	0.21	0.05	0.25
Adjusted Pseudo-R^2	0.00	0.19	0.04	0.23
ACR	0.61	0.85	0.70	0.88

cDtD values for horizons of 3 months or more are significant. This implies that the additional information from the market that is relevant to explain worsening financial health of a firm, over and above the financial and accounting ratios, are those over a longer horizon.

The signs of the remaining input variables in Models $5-8$ are negative as expected, except for LEVER. Thus, smaller sized firm have higher probability of downgrade than the larger sized firms. Firms in distress are likely to have lower stock prices.[10] Firms with lower cash holdings are likely to be in distress, and firms with lower profitability will likely face a higher probability of downgrade. A positive significant coefficient with LEVER is consistent with the hypothesis that firms with higher leverage are more vulnerable to a rating downgrade.

The behaviour of coefficients on the firm's volatility (VOL) is not as obvious. From the sensitivity analysis in Figure 1, we expect a positive relationship between the probability of a rating downgrade and the level of volatility. However in the model[11] as estimated above, the coefficient comes out to be negative, which is counter to our expectation.

Models $7-8$ also include adjustments for firms that have a majority share by the government. The "public sector" nature of a listed firm is a phenomenon that is commonly observed in developing economies such as India. An important reason for including this variable in the probit model for the probability of credit rating downgrades is that such firms typically will have more forebearance on default of payments. This is because a deterioration in the health of these firms is very likely to be met by the government injecting capital into the firms. A more general variable differentiating firms in factors influencing the probability of rating downgrades is a dummy for financial firms. This is because the financial health of these firms tend to structurally different from manufacturing firms, since they typically have higher levels of leverage on average. By default, the null expectation is that this variable will indicate a higher probability of rating downgrade.

The results in Table 4 show that the inclusion of these two dummy variables cause noticeable improvement in model performance. The adjusted pseudo-R^2 increases by 4 percent and the accuracy ratio by 3 percent.

The estimates provide mixed support for the hypothesis at the start of the analysis. DGOVT has a negative coefficient that is statistically significant which is consitent with the hypothesis that government owned firm are less likely to be downgraded. On the other hand, the coefficient on DFIN also turns out to be negative, much against the simplistic notion of high leverage being an indicator of higher probability of default, and thus, a higher probability of downgrades.

[10]Inclusion of EXRET did not improve the explanatory power of our model, we hence, exclude it from our final set of models.

[11]Following the recent literature (Shumway, 2001; Chava and Jarrow, 2004; Campbell et al., 2008), we also estimate a dynamic panel logit model. The results however remained the same.

However, since this is a regression for probability of credit rating downgrades, and sample have no instances of rating downgrades for financial firms, the regression results are likely reflecting the sample characteristic for financial firms. Another reason could be that the financial firms in the sample are also public sector firms, which could also explain the negative coefficient sign.

In summary, our analysis show that there is information in the changes of DtD that can explain increases in the probability of a rating downgrade. These results suggest that DtD changes calculated over periods of the previous three months, upto a year, can signal that a credit rating downgrade for a given firm has become more probable. Further, since the DtD is a measure that can be calculated at a frequency that is higher than most traditional models of credit risk evaluation, the results of such models can be built into risk monitoring systems with more frequent upgrades than traditional models that typically upgrade credit risk measures over a year. The results also show that there is a substantial improvement in the performance to predict the probability of rating downgrades when these high frequency changes in DtD values are used in combination with lower frequency accounting ratios and other financial variables.

5.3. Model behaviour after the 2008 liquidity crisis

One of the consequences of the 2008 global financial crisis has been a loss in faith of then prevalent approaches to security valuation and models of risk measurement. This is likely to have led to changes in the way that financial market practitioners and regulators approach measuring the credit risk of portfolios, or the models that are in place to measure this risk. Table 2 show that the majority of downgrades (as well as upgrades) took place in the sample after the start of the crisis. This period is defined from July 2007 to Jan 2012. In this section, we re-estimate the model estimated in the previous section using data on rating downgrades solely from the this post-crisis period.

The results presented in Table 5 are qualitatively similar to the same models estimated for the full sample period in Table 4. Model 9 estimates the model with the changes in DtD over a year using a series of non-overlapping changes. Model 10 includes the dummy variables that are specific to emerging markets (DGOVT and DFIN). Finally Model 10 and 12 additionally firm specific market and accounting based measures as in Models 6 and 8.

The results show that the relevance of the DtD changes over the previous three months to effect the probability of a rating downgrade is consistent in both periods, before the crisis and after. Most of the accounting ratio variables remain consistent in the post-crisis period. What has changed are the coefficient for FSIZE and the coefficient for DFIN both of which have become insignificant. One explanation could be that larger sized firms were considered to have low credit risk before the crisis. However, after the crisis, the perception of the safety of capital of perception has changed. Thus, there is no longer a premium to the probability of a downgrade that is attributed to larger firms compared with

Table 5 Probit model results for the periods post the 2008 crisis

The table presents the results of estimation using data only for the period after the start of the crisis, from July 2007 to Jan 2012. Model 9 contains only the set of DtD at different non-overlapping intervals so that they cover all the changes in DtD over a one year period prior to a rating change. Model 11 includes the dummy variables of DGOVT and DFIN that captures the specifics of emerging market economies. Model 10 and 12 include the firm specific accounting ratios and market measures along with the changes in DtD, the first model without and the second with the dummy variables.
The values in parentheses are standard errors. Boldface values indicate coefficient estimates that are significant at $p < 0.05$.

	Model 9	Model 10	Model 11	Model 12
Intercept	**-1.57**	**1.11**	**-1.45**	0.68
	(0.05)	(0.40)	(0.05)	(0.45)
cDtD_{-1M}	**-0.39**	-0.27	**-0.48**	-0.32
	(0.19)	(0.29)	(0.21)	(0.30)
$\text{cDtD}_{-(3M-1M)}$	-0.13	**-0.52**	-0.17	**-0.50**
	(0.11)	(0.20)	(0.12)	(0.21)
$\text{cDtD}_{-(6M-3M)}$	-0.16	**-0.33**	-0.18	**-0.34**
	(0.10)	(0.16)	(0.11)	(0.17)
$\text{cDtD}_{-(12M-6M)}$	-0.03	**-0.24**	-0.04	**-0.25**
	(0.07)	(0.11)	(0.07)	(0.11)
FSIZE_{-1M}		**-2.88**		-1.82
		(1.07)		(1.02)
LEVER_{-1M}		**0.96**		**1.97**
		(0.31)		(0.40)
VOL_{-1M}		**-1.42**		**-1.36**
		(0.34)		(0.36)
PRICES_{-1M}		**-1.30**		**-1.12**
		(0.20)		(0.22)
NIMTA_{-1M}		-1.74		-1.35
		(3.48)		(3.35)
CASHMTA_{-1M}		**-0.01**		**-0.01**
		(0.01)		(0.01)
DGOVT			**-0.69**	-0.22
			(0.28)	(0.36)
DFIN			-4.42	-5.29
			(84.56)	(113.41)
log L	-399.30	-303.50	-368.60	-276.06
pseudo-R^2	0.01	0.20	0.07	0.25
Adjusted pseudo-R^2	0.00	0.17	0.05	0.22
ACR	0.61	0.84	0.70	0.87

smaller firms. What is unexpected is the lack of significance of the coefficients for financial firms. The strong negative coefficient has now become insigificant, even though the sign remains the same. In this case also, we can interpret this as a change in the perception that financial firms are safe from undergoing a downgrade in their credit rating.

Another observation in the comparison between the estimates in Tables 4 and 5 is that the magnitude of the coefficients on the cDtD have risen in the period post-crisis, and that on the accounting ratios have reduced. Despite these changes, the accuracy ratio of the models estimated is only marginally lower in the period post the crisis compared to that after. Thus, the information used to assess the probability of a credit rating downgrade in the pre-crisis period contributes equally in the period post the crisis. We infer that there has been no structural change in how the credit quality of firms are done before or after the credit crisis. Moreoever, the evidence suggests that during periods of systemic vulnerability, there is a greater dependence on some summary market information that is being captured in the change in DtD for the credit rating downgrades, and less on the directly observed single factors such as size or volatility of the firms.

This implies that there is an even greater role for the high frequency market based measures to update probabilities of credit rating downgrades during systemic crisis like the 2008 global financial crisis.

6. Conclusion

The credit rating of a firm plays several important roles in finance: from being used as an indicator of credit worthiness based on which the firm can obtain financing, to helping fund managers to allocate funds across different debt investments, to helping regulators to assess the amount of credit in a particular financial sector or the overall system. However, there have often been concerns on the timeliness of the information contained in credit ratings, and these concerns have been escalating over the last decade or two. Although there are rigorous efforts underway to reduce the dependence of credit risk evaluation on credit ratings, credit ratings remain a universally accepted measure based on which the financial industry agrees to evaluate credit risk.

Given this continued dependence until a better alternative can be found to replace ratings, this paper seeks to determine if more timely measures can be calculated that can then be used to predict the probability of changes in credit ratings. This could solve some criticality of the use of ratings in the fund management industry today.

We use data on credit ratings, market price information and accounting ratios for listed firms to answer two questions: (1) Do the higher frequency measures like market prices indicate upcoming changes in the financial health of the firm as measured by the credit rating? (2) Create a model where these higher frequency measures can be used as input to improve the probability of a credit rating downward in the immediate future before the rating is announced.

A non-parametric event study of the levels of average DtD in an event window of 120 days before and after credit rating downgrades find that changes in market based measures like distance to default (DtD) can indicate information of changing financial health faster than the rating agencies update credit ratings.

We use a parametric approach of using probit models where the changes in DtD are used as input along with traditional accounting ratios and financial variables to model the probability of a rating downgrade. We find that changes in DtD begins to capture an impending credit rating downgrade, from about 12 months in advance of the downgrade announcement. Our results suggest that variables like changes in DtD over a 12 to 1 month horizon prior the rating change, ownership of the firm and one month lagged values of firm size, leverage, volatility, prices and cash balances of the firm add significantly to the explanatory and predictive power to forecast upcoming changes in rating downgrades.

The results of this paper are consistent with earlier studies that find that market and accounting measures can predict the probability that the firm's financial health is worsening. What is new is that rather than the level of the DtD, changes in DtD over periods in the immediate past help to update the probability of a downgrade with higher frequency than can be done based on updates of the accounting measures. Such measures becomes even more critical during periods of market crisis, and can prove very useful for fund managers with debt investments in their portfolio.

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