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Abstract

Distance-to-default (DtD) from the Merton model has been used in the credit risk literature, most successfully as an input into reduced form models for forecasting default. In this paper, we suggest that the change in the DtD is informative for predicting change in the credit rating. This is directly useful for situations where forecasts of credit rating changes are required. More generally, it contributes to our knowledge about reduced form models of credit risk.

Keywords: Distance to Default, rating downgrades, rating change, forecasts, event study analysis, probit models, simulation, bootstrap, crisis analysis.

JEL Code: C53, C58, G14, G17, G21

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Distance-to-default (DtD) from the Merton model has been used in the credit risk literature, most successfully as an input into reduced form models for forecasting default. In this paper, we suggest that the *change* in the DtD is informative for predicting *change* in the credit rating. This is directly useful for situations where forecasts of credit rating changes are required. More generally, it contributes to our knowledge about reduced form models of credit risk.

*The authors belong to the IGIDR Finance Group, `http://www.igidr.ac.in/FSRR`.
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Contents

1 Introduction

Credit ratings have been widely used as a component of the investment process, based on the voluntary choices of money managers and on the requirements of financial regulators. At the same time, credit ratings tend to be slow in catching up with information about firms. As an example, the share price of Enron had dropped to $3 when it dropped below investment grade. This motivates the exploration of the possibility that *information from the stock market could potentially be useful in anticipating changes in credit ratings*.

At a conceptual level, Merton (1974) offered a strategy for thinking about credit risk where equity is viewed as a call option on the assets of the firm. The Merton framework yields the Distance-to-Default (DtD) that can be computed in real-time based on stock prices. While the Merton model is informative, in recent years it has become increasingly clear that reduced form models, where there is a combination of accounting data and measures derived from stock prices and structural models such as the DtD, work best (Campbell *et al.*, 2011).

In this paper, we examine the possibility that *changes* in the DtD are an early warning of the *change in the credit rating* of the firm. This is an incremental modification of the reduced form literature, which has utilised information from the Merton model.

Our empirical analysis, based on data for a group of firms observed for over a decade in India, suggests that this is indeed the case. It has two implications. At a practical level, it offers a mechanism for speculators and money managers to anticipate future credit rating changes. Conceptually, it presents a new approach through which the information derived from structural models can become useful in constructing reduced form models.

The analysis is focussed on the top 500 listed firms in India over a long time period of Jan 2000 to December 2011, where the DtD is calculated daily for each firm in the sample. The paper tests the relationship between changes in DtD and changes in credit ratings using two approaches.

The first approach uses an event study framework, based on the event of credit rating downgrades, upgrades and reaffirmations separately. The cumulated DtD takes the place of the Cumulated Average Return that is used in the standard event study literature. The analysis shows that there is a significant and positive change in the DtD before a credit rating upgrade, as well as a reaffirmation. In contrast, there is a sharp drop in the DtD around 25 days prior to a credit rating downgrade. However, the sample size for downgrades is too small to support strong significance of the results.

The second approach adopted is that of a probit model explaining the credit rating change, where changes in the DtD over various horizons are used as explanatory variables. This shows that a change in the DtD from a period spanning three months before the rating downgrade are statistically significant. A sharp drop in the DtD is a useful predictor of a credit downgrade in the coming three months.

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.

2 The toolkit of credit models

The traditional approach to assess the financial health of a firm has been to use information from the balance sheet of firms. Certain accounting ratios were identified that could discriminate between firms with good financial health versus poor financial health (Altman, 1968; Ohlson, 1980; Zmijewski, 1984). These models typically employed multivariate discriminant analysis and multinomial choice models to estimate the probability that a firm would default over one-year using accounting ratios of the previous year.

However, despite a consensus on the accuracy of prediction achieved with using accounting data Altman and Katz (1976); Kaplan and Urwitz (1979); Blume *et al.* (1998), these empirical models have been criticised on a number of issues:

1. The absence of a 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 only, thus fail to capture changes in the financial conditions of the borrowing firm.

3. Period of the forecast: One of the methodological criticisms is that these models are single period models and introduce sample selection bias generating biased and inconsistent coefficient estimates (Shumway, 2001; Chava and Jarrow, 2004).

Of these, the timeliness of information has posed the greatest concern for the use of these models for the credit risk manager for whom the management of risk is done far more regularly than firms update their accounting information. In response, there has been an emphasis on how more real-time information can be used to assess the financial health of firms. One source of such informaiton for firm that are listed and traded in public markets are observed market prices and volatility of their securities, either bonds or equity.

The best known models developed measures of financial health based on equity prices. Merton (1974) developed a structural default model which views equity as a call option on the company's underlying assets under the assumption of limited liability. The approach was refined by subsequent papers like Vasicek (1984) and Crosbie and Bohn (2003) on how the Merton (1974) approach could be deployed to use equity prices to measure financial health. Crosbie and Bohn (2003) proposed the "distance to default (DtD)" measure, which is calculated as the difference between the asset value of the firm and the face value of its debt and scaled by the volatility of the assets of the firm. The measure suggests how many standard deviations is a firm away from default.

The advantage of using securities market prices to assess the financial health is that it addresses both the criticism of not being a measure from a structural model as well as the timeliness of information used in assessing financial health. Securities prices also have the advantage of being a consensus view from the public market which ideally would be an aggregate of all the available information about a firm. Thus, equity market prices could be considered robust observation about the firms financial health that also respond more quickly to events that result in the deterioration of the financial health of a firm.

These models also came with disadvantages. Not all firms that were in credit portfolios of financial institutions and individuals were necessarily listed on public markets for which prices could be observed in real-time. Unlike accounting variables which can be observed for all registered firms. Furthermore, the quality of the prices depended upon how well the securities were traded, how robust was the market microstructure to manipulation, etc.

The DtD has been found to have power in predicting deteriorating financial health at a point in time across firms. Vassalou and Yuhang (2004) found that DtD (market based measure) is a powerful measure to predict bankruptcy. Both Oderda *et al.* (2003) and Kealhofer (2003) examined the predictive ability of DtD compared to credit ratings, and found that the DtD measure predicts rating changes, well in advance of the rating change. In another study, Gropp *et al.* (2006) analyse the ability of DtD and bond spreads to signal fragility of European banks. They found that DtD can predict the probability of a rating downgrade of a bank 6 to 18 months in advance of the downgrade itself.

A comparative analysis of these two approaches of accounting data and market data is presented in Hillegeist *et al.* (2004) and Agarwal and Taffler (2008), who find that the DtD can be a powerful proxy to determine default. However, they also record that there is information in the traditional accounting information and should be used in conjunction with the DtD to forecast default. This approach is also consistent with statistical theory which suggests that, when faced with two estimators for the same underlying variable, it is optimal to combine the two estimators.

Campbell *et al.* (2008) and Bharath and Shumway (2008) incorporate a hazard modelling approach that was first proposed by Shumway (2001), and use both accounting as well as market variables in the estimation. They find that the DtD measure has relatively little explanatory power over the other variables they include in their models. Campbell *et al.* (2011) identify an alternative set of market measures such as *price levels*, *volatility of returns*, *equity to book ratio* and *profitability* that enhance the predictive power of the models for probability of default.

In order to test the performance of the different models, it is necessary to select the benchmark measure of credit quality against which the model output has to be compared. In most of the literature, the dependent variable is a credit event, which is either the event of firm bankruptcy, or a change in the credit rating of the firm's bonds. In the case of bankruptcy, there is significant variation in what constitutes the definition of bankruptcy in different countries. In emerging economies, the definition of bankruptcy becomes even more tenuous. The advantage of using the credit rating change as the credit event is that there is much more homogeniety in the process that generates credit ratings, and changes in credit ratings, given that there are a small set of credit rating agencies that operate across the world.

Thus, despite the criticisms on whether credit ratings show a timely responses to changes in the credit health of a firm, these ratings are typically the only direct measure that is publicly available in most emerging market economies which have weak legal and enforcement framework for bankruptcy. We choose to focus on the change in the credit rating as the credit event in this paper.

Next, we analyse whether the DtD can predict changes in credit ratings for listed firms in India. More specifically, we test if *changes in the DtD* over a given interval of time can predict a rating change. If so, the DtD could be of use to manage credit risk in portfolios of large financial institutions such as banks, insurance companies and pension funds 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.

We test the relationship between change in ratings and change in DtD for rating changes, using two approaches:

1. Event study analysis, where the event is either a credit rating downgrade or an upgrade and the observed variable is the change in DtD before the event takes place, and over varying interval sizes. For example, the observed variable could be the change in the DtD over the last one month before the credit event. Or the change in the DtD for the last quarter before the credit event, etc.

2. Probit model analysis, where the independent variable is the binary variable of a credit rating downgrade or not, or a credit rating upgrade or not. As in the case of the event study, the explanatory variable is the change in DtD over a fixed interval before the credit event, such as a 30-day change or the change over the previous quarter. In addition, other market based measures such as market capitalisation and equity volatility of the firm are included in the estimation.

In both cases, the objective will be to test the hypothesis of whether a change in DtD over any time can predict the credit rating downgrade or upgrade. In both cases, there are some methodological issues that need to be resolved to interpret the analysis as applied to DtD as the variable under examination. These are covered in the following section.

3 Methodological issues

Both the approaches of the event study and probit model estimation are well-established in the literature. What is not as well known is the expected behaviour of the distribution of DtD or changes in DtD. 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 Performance evaluation: Event study

Traditionally, event studies have been used to study the impact of corporate announcements on equity returns. For each in a set of firms that undergo a fixed type of corporate action / announcement, the DtD is calculated each day, and then cumulated each day till 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 250 days. For each firm in the sample that was downgraded/upgraded/reaffirmed, we calculate the cumulative change in DtD (cDtD) over the length of window before t = 0 and after t = 0 as:

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

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

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 Performance evaluation: probit

We also estimate a probit model to estimate how much the change in DtD at different intervals can predict a rating change. We start with a simple specification where there is only one exogenous variable used. The variable used is the change in the DtD over a fixed time horizon as:

$$Pr(Y_i = 1) = \phi(\beta_0 + \beta_1 \Delta\mathrm{DtD}_{i,-N})$$

where

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

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 was a rating downgrade for the bonds of firm i and 0 if there was a rating upgrade or reaffirmation.

ϕ represents the cumulative normal distribution. $\Delta\mathrm{DtD}_{i,-N}$ represents the change in DtD N days prior to the rating change date. Thus, $\Delta\mathrm{DtD}_{i,-1M}$ implies change in DtD of firm i over a one-month period prior to the day of the rating change. We estimate the model at different values of N, where $N = 1$ month, 3 months, 6 months and 12 months from the day of rating change day.

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

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

$\Delta\mathrm{DtD}_{i,-(3M-1M)}$ 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 Interpreting distance to default

The Merton (1974) framework uses the Black-Scholes (B-S) option-pricing model to establish the link between the market value of the assets of the firm and the market value of its equity. Equity is taken as a call option on the assets with the equity holders being the residual claimants of the assets after debt obligations are met.

In the Merton (1974) framework, the value of the firm V_A and the volatility of the firm value σ_A is solved by using a two-equation system involving the standard call option pricing equation where the equity value of the firm is the call option price, and one more equation linking σ_E and σ_A as $\sigma_E = \frac{V_A}{V_E}\Delta\sigma_A$.

Once these have been solved, the distance to default (DtD) is calculated as:

$$\text{DtD} = \frac{V_A - X}{V_A \sigma_A}$$

where X is the book value of the debt that is due at time T.

Interpreting DtD across firms

DtD can be interpreted as how many standard deviations the asset value of the firm is away from the debt of the firm. The standardisation by both the size of the firm and volatility of the firm value means that the DtD can be used to rank firms in terms of their credit quality. Thus, even where data on actual defaults or bankruptcies are not readily observed, the DtD retains its usefulness as a relative measure of credit worthiness of firms in a given sample. At any given point in time, across firms in a sample, the closer DtD of a firm is to zero, the closer the firm is to default compared to firms whose DtD values are further from zero.

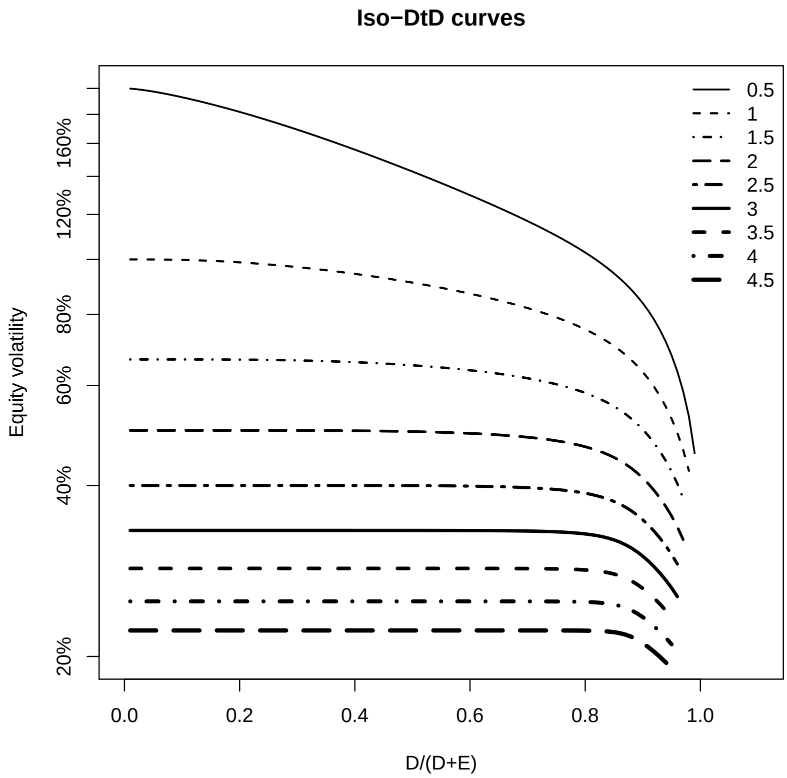
Interpreting DtD across input variable characteristics

Three key inputs to 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.

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.



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 only starts changing (dropping towards zero) significantly only for much higher levels of leverage (beyond 80 percent). For a constant level of leverage, DtD shows much sharper 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 interesting 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, in 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. Whereas these same changes in leverage during systemically calm periods would have generated smaller decreases in DtDs. Thus, the interpretation of changes in DtDs have different implications on changes in firm credit quality during periods of high and low volatility.

This suggests that when DtD changes are included in the probit model as explanatory variables, both leverage and volatility measures should be included as well to sharpen the identification.

Implications for the probit model specification

This above understanding about changes in DtD implies that the changes in DtD may have a different implication for possible future changes in the rating depending upon a few other market based features of the firm. This links to similar suggestions made in the literature on the use of other market-based measures (Campbell *et al.*, 2011). In our model, we use:

1. Firm size ($\textsc{fsratio}_{i,t}$): 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,
2. Leverage ($\textsc{lever}_{i,t}$): measured as the ratio of total debt of the firm (sum of short term and long term debt) to its equity (measured by market capitalisation),
3. Volatility ($\textsc{vol}_{i,t}$): measured as the historical volatility in the equity prices of the firm over the past 1 year.

We include the lagged values of all these three variables, one month prior the rating change. Firm characteristics are added to the univariate as well as the multivariate model. The full multivariate model, including firm characteristics, is now specified as:

$$\begin{aligned} Pr(Y_i = 1) \;\; &= \;\; \phi(\beta_0 + \beta_1 \Delta\mathrm{DtD}_{i,-1M} + \beta_2 \Delta\mathrm{DtD}_{i,-(3M-1M)} \\ &\quad + \beta_3 \Delta\mathrm{DtD}_{i,-(6M-3M)} + \beta_4 \Delta\mathrm{DtD}_{i,-(12M-6M)} \\ &\quad + \mathrm{FSRATIO}_{i,(-1M)} + \mathrm{VOL}_{i,(-1M)} + \mathrm{LEVER}_{i,(-1M)}) \end{aligned}$$

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.

Model selection

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).
- 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.
- The third is the *false negative rate* (FNR) computed as the ratio of the number of firms that went a downgrade but was not predicted by the model to the total number of downgrades. High FNR values will indicate that the model fails to predict higher probability of downgrade.

4 Data

Table 1 Summary statistics of average market-based measures

The table reports the summary statistics of the market capitalization weighted average market cap, equity volatility, and DtD. Equity volatility is the historical volatility of returns over the past 250 days.

	Market capitalisation (Rs. trillion)	Equity volatility (in %)	Leverage	DtD
Min	2.94	35	0.09	1.62
Q1	4.80	43	0.17	1.92
Median	11.15	51	0.23	2.13
Mean	21.91	50	0.27	2.21
Q3	39.14	56	0.37	2.55
Max	69.45	66	0.62	3.04

The analysis focuses on the top 500 firms by market capitalisation and liquidity that are listed on the National Stock Exchange, India. The period of the analysis is between April 1997 to January 2012. Table 1 presents the summary statistics on the the market based measures including market capitalisation, leverage and equity volatility.

4.1 Distance-to-Default (DtD)

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

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)[1] and the floating stock of shares outstanding.[2]

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.[3]

4. Strike or 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 *short term liabilities* are calculated as the sum of a set of short-term borrowings listed in the balance sheet of the firm.[4] The *long term liabilities* is calculated as the difference between *total borowings* and *short term liabilities.* The data is available at annual frequency. For the purpose of the analysis, we have assumed that the liabilities for the firm remains the same for the financial year.[5]

5. Time: Maturity of one year.

[1] `http://www.nse-india.com`

[2] These were extracted from the Prowess database on firms, published by the *Center for Monitoring Indian Economy* (CMIE). `http://www.cmie.com`

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

[4] These have also been taken from the Prowess database. The exact list of variables is listed in Appendix A.

[5] For the Indian data, the financial year spans from 1^{st} April to 30^{th} March of the following 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 500 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 have been computed based on daily market capitalization weights of the sample firms.

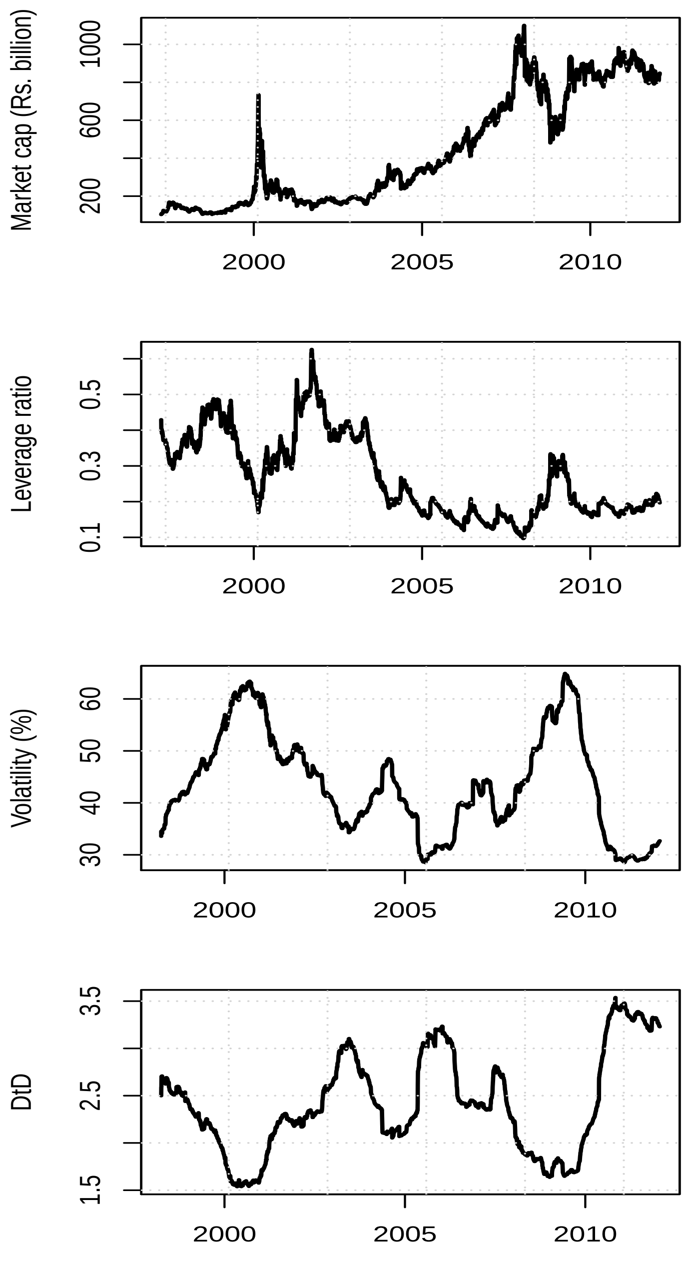


Figure 2 plots the weighted average values of the four market based measures for the firm used in this analysis: market capitalsation ratio, volatility, leverage and DtD.

We see a sharp fall in the value of distance to default during the 2008 financial crisis period. What is more interesting is that these changes follow a near one-to-one inverse relation between average DtD and average volatility. This indicates a very strong relation between DtD values and volatility. This in accordance with our understanding of how the DtD values need to be interpreted when the volatility and leverage in the market is higher or not, from the simulation in Figure 1. During periods of high volatility, the same amount of change in DtD could likely have a different implication on the financial health of the firm compared to if the market was less volatile.

4.2 Credit events

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
Downgraded	0	4	1	0	0	1	0	0
Reaffirmed	23	98	124	164	211	212	208	175
Upgraded	0	0	0	0	2	1	0	5
	2005	2006	2007	2008	2009	2010	2011	Total
Downgraded	0	0	0	0	4	3	16	29
Reaffirmed	219	306	286	312	524	674	562	4098
Upgraded	2	1	2	1	10	39	40	103

The available ratings data contains the initial rating and all the rating change on debt instruments. Table 2 presents the rating changes for the firms in the sample. There are about 4230 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.

5 Results

5.1 Event study analysis

Table 3 Average cumulated change in DtD before and after rating change

The table shows the average cumulative change in DtD over a 250-days period before and after the announcement of a rating change. The cumulative change has been computed as described in Section 3.1.

	Upgrade	Downgrade	Reaffirmation
Before rating	0.38	-0.11	0.24
After	0.23	-0.08	0.23

Table 3 presents the average cumulated change in DtD for each set of firms that underwent a rating upgrade, a rating downgrade as well as reaffirmation in the sample. The event window is defined as around 250 days before and after the rating change announcement. Just preceding the day of ratings announcement, the table shows that DtD rises (falls) significantly for upgrades (downgrades), indicating it does capture some information prior the rating agency response. After the rating change announcement DtD does rise (fall) after an upgrade (downgrade). However, this rise (fall) is less than the pre announcement change. A change in DtD post announcement is indicative of DtD reacting to credit rating announcements

Figure 3 Average change in DtD 250 days before and after a rating change

The graphs shows the behavior of average cumulated change in DtD for the sample firms that went an upgrade, downgrade or a reaffirmation 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. However, the band has a postive skew in the pre-downgrade period, and a negative skew in the period after the rating downgrade.

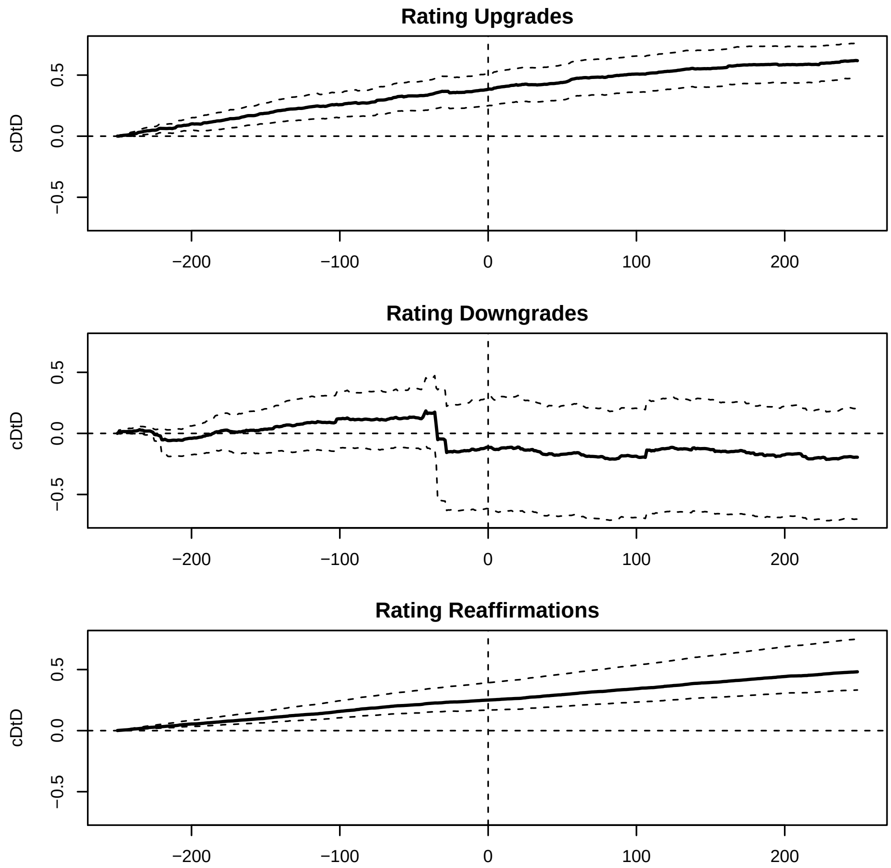


Figure 3 plots the cumulative values along with the 95% bootstrap confidence intervals, for the sample of firms which were downgraded, upgraded or reaffirmed.

The first panel shows the average cumulative cDtD for the firms that were *upgraded*. There is a significant increase in DtD around rating upgrades, both before and after the credit rating change. The bootstrap confidence intervals clearly lay above the zero line, which implies that the changes in DtD are significantly large. Post the rating change event however, the change in the DtD becomes smaller and smaller on a day to day basis, indicating that the increase in DtD reduces significantly after the rating announcement change.

The second panel shows the same picture for the sample of the firms that were *downgraded* during the study period. The cumulative cDtD shows a significant *fall* 25 days prior the credit rating downgrade, indicating a possibility of DtD capturing a deterioration in a firm's health approximately one month prior to the rating agency's assessment. After the rating change event, DtD stabilizes at a lower value. However, the wide confidence interval for cumulative DtD change suggests that the inference should be drawn with caution. The third panel shows the average cumulative DtD change for the firms which were accredited the reaffirmation status. There is a small (insignificant) rise prior the rating announcement in DtD.

5.2 Probit analysis

Table 4 reports estimates for the probit models specified in Section 3.2. The output of these models is the probability of a rating downgrade for a given firm. The first four models (Models $1 - 4$) have a single horizon change in DtD as the explanatory variable. Among these four models, Model 3 has the "best" performance measures, with the highest pseudo-R^2, highest ACR and lowest FNR.

The value and signs on the estimated coefficients offer some interesting insights. The coefficients associated with change in DtD over all horizons are all negative, which is consistent with the expected inverse relationship between changes in DtD and rating changes. When the DtD decreases (goes closer to zero), it implies that the credit quality of the firm has worsensed which, in turn, implies an increase in the probability of a downgrade. Of these, the change in DtD over the previous one month has no significance in explaining a rating downgrade. However, all changes over a three month horizon has significant coefficients. This suggests that there is some predictive power in the changes in DtD for a rating downgrade. Except for the DtD changes over the last month. This implies that the market DtD measure adjusts more a month prior to the rating downgrade.[6]

[6] Gropp *et al.* (2006) found similar results. They used levels DtD data to determine if DtD can predict downgrades, and found that at the interval closer to the default (three months in their case), the coefficient came insignificant. They attributed the reason to be increased noise in the months closer to the default/downgrades.

Table 4: Probit estimates based on DtD changes over different horizons

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	**-2.48**	**-2.50**	**-2.51**	**-2.48**	**-2.45**	**-2.29**	**-2.20**	**-2.12**	**-2.48**
	(0.07)	(0.08)	(0.08)	(0.08)	(0.25)	(0.27)	(0.29)	(0.32)	(0.25)
ΔDtD_{-1M}	-0.53				-0.44				
	(0.36)				(0.37)				
ΔDtD_{-3M}		**-0.40**				**-0.38**			
		(0.12)				(0.13)			
ΔDtD_{-6M}			**-0.33**				**-0.35**		
			(0.11)				(0.13)		
ΔDtD_{-12M}				**-0.22**				**-0.26**	
				(0.10)				(0.12)	
FSRATIO_{-1M}					**-0.76**	**-0.74**	**-0.67**	**-0.68**	**-0.78**
					(0.41)	(0.41)	(0.39)	(0.39)	(0.41)
LEVER_{-1M}					0.03	0.01	0.00	0.01	0.03
					(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
VOL_{-1M}					0.20	-0.11	-0.34	-0.45	0.25
					(0.45)	(0.50)	(0.55)	(0.59)	(0.44)
log L	-131.54	-127.23	-117.59	-118.38	-117.55	-114.00	-104.85	-105.34	-133.27
pseudo-R^2	0.01	0.04	0.11	0.10	0.04	0.07	0.14	0.13	0.04
ACR	0.51	0.57	0.60	0.59	0.70	0.69	0.69	0.69	0.73
FNR (%)	86	64	64	71	50	61	61	61	54

The next four modes (Models 5−8) have both the changes in the DtD measure over the four different horizons *and* three other market-based measures for the firm: size (FSRATIO), leverage (LEVER) and volatility (VOL).

Here, the performance measures are not as clear. By the pseudo-R^2 measure, the "best" model is Model 7 or 8 which has the change in DtD over the three or six month interval along with the other market-based measures. These values of pseudo-R^2 are slightly better than the single variable models 3 or 4.

Model 9 has been presented as a benchmark model to present the performance and estimates value without any information about the changes in DtD. We find that the explanatory power of the model falls substantially to pseudo-R^2 of 4 percent, indicating that DtD qualitatively adds incremental information to the model outcomes.

However, it must be noted that the "best" ACR / FNR performance, which relates more to the identification of the firms that suffer a downgrade or not, is from Model 5, which has significantly better values of both ACR and FNR compared to the other models in the set. While the comparison is not as straightforward, Model 5 shows similar ACR / FNR performance to Model 9 which presents the results of the model with only other market measures *not including* the change in DtD values.

Among Models 5 − 8, the signs on the estimated coefficients on the changes in DtD having negative coefficients in this set as well. Even with the other market based measures, the change in DtD from the 3-month horizon and above remain significant. Thus, we can say that the change in the DtD remains consistently influential in predicting a rating downgrade.

With regards to the other market based measures, only the size variable FSRATIO of the three is somewhat significant (at 10% level of significance). However, both FSRATIO and LEVER have the correct signs on the esimated coefficients. FSRATIO has a negative coefficient which impiles that the lower the firm size, the higher the probability that the firm rating will be downgraded comparison to larger sized firms. LEVER has consistently positive coefficients, which is also consistent with our expectation that firms with higher leverage will be more vulnerable to a rating downgrade.

The behaviour of coefficients on the volatility variable is not as clear. When the coefficient on the change in DtD is significant, the coefficient on VOL is negative. However, when the change in DtD coefficient is not significant (as when the horizon of the change used is from one-month prior to the rating downgrade), the coefficient is positive. From the sensitivity analysis in Figure

1, we would expect a positive relationship between the probability of a rating downgrade and the level of volatility. In fact, even though VOL coefficient is not significant in Model 9, the sign is positive. One reason could be that both leverage and volatility are inputs into DtD calculation, and perhaps their effect is already captured in DtD changes.

Table 5 Probit using non-overlapping DtD changes over the previous year

The two models here include all the changes in DtD from the date of the rating change to one year out. Model 1 has all the changes in DtD over non-overlapping intervals. Model 2 additionally contains the other three market-based measures capturing firm size (FSRATIO), leverage (LEVER) and volatility (VOL).

The values in parentheses are standard errors. Boldface values indicate coefficient estimates that are significant at $p < 0.05$.

	Model 10	Model 11
Intercept	**-2.51**	**-2.25**
	(0.08)	(0.35)
ΔDtD_{-1M}	-0.10	-0.06
	(0.39)	(0.37)
$\Delta\text{DtD}_{-(3M-1M)}$	**-0.47**	**-0.37**
	(0.15)	(0.14)
$\Delta\text{DtD}_{-(6M-3M)}$	0.04	-0.08
	(0.26)	(0.24)
$\Delta\text{DtD}_{-(12M-6M)}$	-0.04	-0.03
	(0.17)	(0.18)
FSRATIO_{-3M}		-0.54
		(0.28)
LEVER_{-3M}		0.02
		(0.04)
VOL_{-3M}		-0.33
		(0.70)
$\log \text{L}$	-100.55	-89.08
pseudo-R^2	0.12	0.14
ACR	0.70	0.69
FNR (%)	71	43

Table 5 presents the estimated coefficients when all the changes in DtD are used, where each change is non-overlapping with the other. Put together, the four variables ΔDtD_{-1M}, $\Delta\text{DtD}_{-(3M-1M)}$, $\Delta\text{DtD}_{-(6M-3M)}$, $\Delta\text{DtD}_{-(12M-6M)}$ cover all the changes in the DtD of the firm for one year before the rating change. Model 10 only has the changes in DtD, while Model 11 has both the changes in DtD as well as the three market measures for the firm.

As opposed to the results in Table 4, we see that the coefficients of DtD changes turn insignificant for all except the $\Delta\text{DtD}_{-(3M-1M)}$. This means that the DtD changes from one month prior a rating change vis-a-vis three months prior rating changes captures deterioration in firm's health, and can predict change in downgrade. As we saw in Table 4, we again see that the coefficient with FSRATIO_{-3M} comes out to be significant at 10% level of significance. Also as in Table 4, the sign on all the coefficients are on par with expectations, except for the VOL coefficient which is negative.

The pseudo-R^2 value also turns out to be higher than the values reported in Table 4. Model 11 turns out to be the best model with the maximum log likelihood value, pseudo-R^2 with 69% accuracy ratio and 43% FNR.

Thus, the above estimations suggest that DtD changes between three and one month prior to the rating change event can predict the probability of a rating downgrade.

5.3 Performance since the 2008 liquidity crisis

Table 6 Probit results for the post crisis period

The table presents the results of estimation using data only for the period after the crisis (July 2007 to Jan 2012). As in Table 5, Model 12 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 13 includes the three firm specific market measures as well as the set of changes in DtD.

The values in parentheses are standard errors. Boldface values indicate coefficient estimates that are significant at $p < 0.05$.

	Model 12	Model 13
Intercept	**-2.34**	**-1.87**
	(0.09)	(0.40)
ΔDtD_{-1M}	-0.13	-0.05
	(0.35)	(0.36)
$\Delta \text{DtD}_{-(3M-1M)}$	**-0.41**	**-0.34**
	(0.14)	(0.15)
$\Delta \text{DtD}_{-(6M-3M)}$	0.09	-0.00
	(0.26)	(0.27)
$\Delta \text{DtD}_{-(12M-6M)}$	-0.05	-0.12
	(0.17)	(0.20)
FSRATIO_{-3M}		-0.34
		(0.30)
LEVER_{-3M}		0.10
		(0.06)
VOL_{-3M}		-0.95
		(0.83)
log L	-86.17	-74.24
pseudo-R^2	0.05	0.07
ACR	0.60	0.74
FNR (%)	57	32

Table 2 showed that the majority of downgrades (as well as upgrades) took place in the sample in the post crisis period, which we defined as July 2007 - Jan 2012. We focus on re-estimating the models of Table 5 only using data from the crisis period. Model 12 estimates the model with the changes in DtD over a year using a series of non-overlapping changes. Model 13 also includes the three market measures for the firm.

We note that the model performance for Model 13 in terms of the pseudo-R^2, ACR and FNR show the best values of all the models estimated so far. This is perhaps unsurprising considering that the information about the ratings changes are strongest in this post-crisis period.

The results presented in Table 6 are qualitatively similar to the same models estimated for the full sample period in Table 5. Once again, the results show that the DtD changes over the previous three months in advance to credit rating agency matter for influencing the probability of a rating downgrade. However, unlike in Model 10 and 11, the coefficient for FSRATIO has become insignificant in Model 12 and 13.

One explanation could be that while larger sized firms were considered to be less vulnerable to credit risk before the crisis, after the crisis, this perception no longer held true. All firms, no matter that they were big or small, were considered vulnerable to higher credit risk, enhancing the perception that the kind of liquidity shocks seen in the 2008 crisis was truly system wide. In such period 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.

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A Components in firm debt

- Secured short-term bank borrowings
- Secured short-term financial institutional borrowings
- Secured domestic supplier's credit of which: redeemable in the current year
- Secured foreign suppliers' credit
- Interest accrued and due (on secured and unsecured borrowings)
- Unsecured short-term bank borrowings
- Redeemable debentures and bonds in the current year (unsecured)
- Unsecured domestic suppliers' credit
- Unsecured foreign suppliers' credit
- Commercial papers

B Credit events by instrument type

Table 7 Instrument wise credit event

	Instrument	Downgrade	Reaffirmation	Upgrade
1	Acquirers/Investors' share/payout in assignment of receivables	1	126	36
2	Bank Guarantee	3	172	3
3	Bill Purchase / Bill Discounting / Bill negotiation	0	10	0
4	Buyer's credit	0	17	0
5	Cash	0	196	5
6	Cash Credit	1	124	7
7	Certificate of deposit	0	473	0
8	Commercial paper	1	1359	8
9	Cumulative non-convertible preference shares	0	1	0
10	Debentures / Bonds / notes / bills	0	2733	2
11	Debt	0	135	2
12	Deferred purchase consideration	0	6	1
13	Export finance	1	0	0
14	First loss facility - securitisation	0	0	1
15	Fixed deposits (including intercorporate deposits)	0	731	2
16	Fixed rate pass through certificate	0	31	2
17	Fixed rate unsecured non-convertible debentures	12	1545	27
18	Fixed rate unsecured partly convertible debentures	2	13	0
19	Floating rate unsecured non-convertible debentures	0	1	0
20	Foreign bill purchase / discounting / negotiation	0	10	0
21	Foreign currency term loan	2	27	0
22	Fully convertible unsecured debentures/bonds/notes	0	4	0
23	Fund based financial facility/instrument	5	129	13
24	Letter Of credit	2	305	5
25	Line of credit	1	22	0
26	Liquidity facility - securitisation	0	108	4
27	Loan receivables (assignment)	0	1	0
28	Long term Loans	21	663	35
29	Medium-term loan	0	19	0
30	Non convertible unsecured debentures /bonds/notes/bills	0	9	0
31	Non-cumulative preference shares	0	1	1
32	Non-fund-based financial facility/instrument	4	342	15
33	Non-fund based working capital limit	1	40	1
34	Others	0	6	1
35	Overdraft	0	8	0
36	Packing Credit	1	35	0
37	Partly Convertible unsecured debentures/bonds /notes/bills	0	1	0
38	Pass through certificates	1	338	29
39	Post-shipment credit	0	8	0
40	Preference shares	0	70	0
41	Pre-shipment credit	0	7	0
42	Second loss facility - securitisation	0	19	32
43	Secured premium notes (SPN)	0	1	0
44	Short-term loan	4	1489	16
45	Term loans	10	378	23
46	Vendor financing	0	3	0
47	Working capital loan	1	75	3