

Informational efficiency of credit ratings

Nidhi Aggarwal*

Manish K. Singh

Susan Thomas

Abstract

The timeliness of the credit rating of a firm has been frequently called into question over the previous two decades. This paper examines whether changes in credit ratings can be updated more frequently than at the frequency of updates in the accounting data. The paper finds that, when market equity prices of firms are readily available, *changes* in high frequency measures such as the Distance to Default, along with low frequency firm characteristics such as ownership structure and accounting data, can provide a more timely update on the probability of credit ratings downgrades.

JEL classification: G21, G24, G32

Keywords: Merton model, event study analysis, logit regressions

*Nidhi Aggarwal is at the Indian Institute of Management, Udaipur. Manish K. Singh is at the Indian Institute of Technology, Roorkee. Susan Thomas is at the O. P. Jindal Business School and XKDR Forum. Authors email: nidhi.aggarwal@iimu.ac.in, mks@hs.iitr.ac.in, sthomas.entp@gmail.com. We are grateful to Tiksha Kaul and Aanshi Sharma for their excellent research assistance at various stages of the development of the work of this paper. We thank Ajay Shah for inputs into the research design, and to participants at the Jindal conference for comments and suggestions on an early draft of this paper. The views expressed in this paper belong to the authors and not their employer. All errors and omissions remain our own.

Contents

1	Introduction	3
2	Questions	5
3	Data	7
4	Event study analysis and results	9
5	Empirical estimation and results	12
6	Robustness tests	16
6.1	Firm characteristics	16
6.2	Rating instruments characteristics	16
6.3	Differences across CRAs	17
6.4	Accounting ratios	17
6.5	Additional checks	18
7	Testing model prediction performance	19
8	Conclusion	23
A	Credit ratings for the period, 1989-2020	26
B	Effect of rated instruments characteristics	27
C	Effect of government ownership	31

1 Introduction

At any given point in time, a credit rating reflects the opinion of a credit rating agency about the probability that a firm will default on its debt obligation. While the role of credit ratings has come under severe criticism,¹ they remain the most widely used indicator of the creditworthiness of a firm. Financial investors continue to base their credit investment decisions on ratings. Furthermore, financial regulators continue to rely on ratings while setting micro-prudential guidelines on investments by financial firms.

The main criticism about ratings is their slow reaction to the deteriorating financial conditions of the borrower. Recent examples in public memory include AIG and Lehman Brothers in 2008, which were investment-grade rating until minutes before the banks collapsed, or similar examples from earlier times with the gap in ratings of Enron and WorldCom and their sharply dropping stock prices in early 2000. Despite this, micro-prudential risk measurement by regulators have continued to depend upon credit ratings (for detail discussion, refer to [White \(2010\)](#)). Given that asset managers are bound to use credit ratings as part of their risk assessment and reporting, development in credit risk research has focused on how to update credit risk measures in a more timely manner.

In line with this domain of research, this paper seeks to test if *changes in DtD* can predict *changes in credit ratings*. This aims to develop a real-time update of credit ratings that can incorporate the changing financial conditions of a firm faster than updates published by credit rating agencies. The approach in the paper is to use the distance to default (DtD) measure based on the [Merton \(1974\)](#) framework. The DtD measures how many standard deviations a firm is away from defaulting in the next one year horizon. The advantage of this approach is that it is based on the equity prices of a firm, and so is updated at a higher frequency than either the credit ratings or the accounting variables that are used in traditional probability of default models.

The paper uses two econometric approaches in its analysis. The first part of the analysis uses a non-parametric approach of an event study to test whether there is a significant cumulative change in DtD of a firm before a rating downgrade. The second part uses a parametric approach of a logit model regression to estimate the probability of a rating downgrade as the function of changes in DtD in the prior periods as the independent variable. Traditional accounting ratios and financial variables along with other firm specific and economy wide variables are also included in the estimation to improve the predictive power of the model.

The sample used for the analysis includes data on 2520 listed firms in India, which are observed over a 12 year period from January 2009 to September 2020. These firms collectively had 90,285 rating revisions during this period, of which 68,857 (76.3 percent) were reaffirmations, 12,669 (14 percent) were downgrades, and 8,759 (9.7 percent)

¹Starting from 2011, the U.S. Dodd-Frank Act stipulates that credit ratings not be used as a measure of credit quality in the risk assessment of financial firm portfolios.

were upgrades.

The event study analysis shows a significant drop in the average prior period DtD before a credit rating downgrade. It also shows that firms can be grouped based on the average DtD of the firm, which indicates that the level of DtD as well as changes in DtD capture information about the evolving health of the firms. There is a significant drop in prior period changes in DtD before the rating downgrade, which suggests that changes in DtD can be useful as a lead indicator to predict a rating downgrade.

The results from the logit regression substantiate these non-parametric insights. At all horizons, the coefficient of a prior period DtD change is seen to be positive and statistically significant for a credit rating downgrade. In the credit model performance measures, the area under the receiver operating characteristics (ROC) curve shows that the full sample average accuracy is 0.62. The addition of the firm characteristics - namely, size, age, and industry - improves the explanatory and predictive power of the model, which is in line with [Campbell et al. \(2008\)](#). A value of 0.75 for the area under the ROC curve improves to 0.77 with the addition of rated instrument characteristics (rating amount, rating instrument, and rating agency), and to 0.81 when we add traditional accounting-based ratios of firms' performance. Across all these estimations, changes in prior period DtD remains a significant variable for rating downgrades.

We conduct robustness checks of these results through a series of tests. First, we test the efficacy of these relationships across the ratings of different maturity instruments. Second, we test separately for investment and non-investment grade instruments. Lastly, we control for the ownership of firms since emerging markets tend to have a significant number of firms where either the government or business groups have controlling stake, both of which have implications for the financial health of the firm. The change in prior period DtD remains a robust and significant predictor of a credit rating downgrade, in all of these cases.

The paper contributes to the literature in three ways. First, the analysis provides evidence that the changes in credit risk of the firm measured by the DtD is consistent with that measured by credit ratings (regardless of the credit rating agencies themselves). And it provides evidence from both event studies and parametric logit model-based approaches that changes in the prior period DtD measures can help predict changes in credit ratings. Second, the logit model results show that significant drops in the DtD in the previous 12 months strongly indicate a high probability of a credit rating downgrade. Finally, this paper adds new evidence to the literature on the ability of changes in market price based DtD measures to be lead indicators of changes in credit ratings of a firm, on a timely basis relative to updated publication of accounting data.

The rest of this paper is organized as follows. Section 2 presents the alternative approaches and how well these models perform. A description of the sample used in the paper is in Section 3. Section 4 presents the results of the event study analysis, and Section 5 the results of the logit regression. Section 7 presents the improvements in

predicting probability of default using the models estimated in the analysis. Section 8 concludes.

2 Questions

Credit risk models have been a research focus in finance for several decades now. These are models to estimate the probability of default of a firm on a payment at fixed time horizon in the future, typically over a year. Credit rating agencies use estimated probabilities of default to create categories of firms with similar financial health. Each category gets a credit ranking or rating. Two approaches create a distinct dichotomy in types of empirical models: statistical models built on the empirical characterization of firms that default relative to firms that do not, and structural models which are developed from a theoretical understanding of why firms default.

The statistical models use information from the balance sheet and other financial reports that are regularly issued by firms to measure the likelihood of bankruptcy (Altman, 1968; Ohlson, 1980; Zmijewski, 1984). While these models are widely used (Altman and Katz, 1976; Kaplan and Urwitz, 1979; Blume et al., 1998), they are criticized on the following grounds:

1. Methodological: that these are single period models, with biased and inconsistent estimates based on the specific sample used (Shumway, 2001; Chava and Jarrow, 2004), and the absence of an underlying theoretical model which is a structural representation of the financial health of the firm.
2. Timeliness of information: financial statements published by firms report past performance, and are available only at either a quarterly or annual frequency. These fail to capture changes in the financial conditions of the borrowing firm, and may be a misrepresentation of the current state of the financial health of the firm.

These criticisms gave rise to the structural models of firm default. Of these, the most widely known is Merton (1974). This models the firm's equity as a call option on the underlying value of the firm. Under the assumption of limited liability, the model uses market price information about the equity and debt of the firm to estimate the value of the firm. The difference between this estimated value and the book value of debt indicates how close the firm is to default. Despite its simplicity and appealing grounding in financial theory, this basic model is based on some well-documented but strong assumptions involving the simple structure of a firm's debt (Agarwal and Taffler, 2008; Bharath and Shumway, 2008). Most notably, it assumes that a firm issues a zero-coupon bond of maturity T , that default only occurs at maturity, and that the statistical distribution of the asset value follows a geometric Brownian motion, which implies that it is log-normally distributed. Nevertheless, the model has attracted much interest among academics and practitioners, and several variants have been introduced in the literature (see Agarwal and Taffler (2008) for comparative analysis).

The principle advantage of [Merton \(1974\)](#) is that the model allows for the financial health of the firm to be calculated at the higher frequency at which market prices are available for equity and debt. The disadvantage is that it can be done only for listed firms that are well traded, compared to statistical models which use accounting variables that are available for all registered firms.

The model was readily made operational to create financial health measures of firms for which equity price are readily available ([Vasicek, 1984](#); [Crosbie and Bohn, 2003](#)). [Crosbie and Bohn \(2003\)](#) proposed the “distance to default” (DtD), which measures how many standard deviations a firm is from default. This measure has, since, become entrenched as an important indicator of firm financial health in real-time. For example, [Shah and Thomas \(2000\)](#) apply this approach to estimate the assets of Indian banks, and estimate that the size of the subsidy provided by the Indian state was around eight percent of GDP. [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.

One branch of the credit risk modeling research compares the performance of accounting data based and market data based measures. There are mixed results on how much more power the DtD has over the information in the accounting data in measuring the probability of firm default. [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. [Hillegeist et al. \(2004\)](#) and [Agarwal and Taffler \(2008\)](#) find that there is considerable improvement in the quality of probability of default 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 the 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 using market data and accounting data 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. In particular, changes in the financial condition as represented by changes in credit ratings. Inherent in this question is the assumption that rating changes capture the changing credit quality of the firm.

Despite the criticisms about credit ratings, they are typically the only publicly available indicator of the credit risk of a firm, and one that is consistently available across all markets. Ratings are especially important as an indicator of financial health in emerging markets that have weak legal and enforcement frameworks for bankruptcy. The impor-

tance 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 failed to provide timely information of the financial health of the firm, lagging behind other measures such as stock market prices of listed securities of firms.

There are various scenarios about why this may be so. Credit rating agencies may be slow to adopt real-time measures of market prices into their ratings models. Alternatively, the lag in rating updates could merely reflect policies on how ratings agencies update ratings. The lack of timeliness of rating changes could be a consequence of the business model of the credit ratings agencies. These agencies are paid for rating debt securities at issuance, but not necessarily for updates of the ratings. This certainly holds in emerging markets where rating updates are done less systematically, and are typically updated only prior to a credit event such as a bankruptcy or a well-defined corporate action like a merger or acquisition. But since ratings are a critical input to prudential rules on fund management, changes in the ratings are widely accepted as a credit event.

Therefore, this paper focuses on changes in credit ratings as the financial health measure of interest, and ask whether changes in the DtD (ΔDtD) over a given interval of time can predict a rating change (ΔCR). The relationship that we test is written as follows:

$$\Delta \text{CR}_{i,T} = \alpha + \beta_i \Delta \text{DtD}_{i,(T,t)}$$

For a firm i , $\Delta \text{CR}_{i,T}$ is the direction of the change in credit rating at T , and $\Delta \text{DtD}_{i,(T-t)}$ is the change in the DtD t periods before T . Then, the hypothesis that we test is as follows:

$$H_0 : \beta_i = 0$$

$$H_A : \beta_i \neq 0$$

If we consider that market information for a listed firm is updated at a higher frequency than the accounting data that is often used by the credit rating agency to estimate the probability of default of the firm, we expect that H_0 is not true. In the next section, we discuss the data used to test this hypothesis, and several complexities in how ratings are published that must be incorporated before the data can be used for this exercise.

3 Data

Our data consists of all credit rating event observations published by seven credit rating agencies that are active from December 1988 to September 2020.² We consider all

²The rating agencies for which we observe ratings are Acuite, Brickwork, CARE, CRISIL, ICRA, IND-RA, and IVR.

non-financial firms for which credit event data is available in the ProwessIQ database published by the Center for Monitoring Indian Economy (CMIE). This gives us a sample of 2960 firms and 133,007 credit events in this period.

The credit events data for this sample has seven different categories of credit events. These are (1) Upgrades; (2) Downgrades; (3) Reaffirmations; (4) Initial rating; (5) Rating watch; (6) Suspended; and (7) Withdrawn. There are also observations which are labelled “Not applicable” or are missing, which we do not include.

Since our analysis focuses on the links between credit rating changes and market based distance to default measures of credit risk, we apply the following two filters to the data. First, we retain only on firm-instrument level observations for credit events of Upgrades, Downgrades and Reaffirmations, and drop the rest from our sample. Next, we retain firms for which market based information is available, which are the firms which are listed on the National Stock Exchange (NSE) or the Bombay Stock Exchange (BSE).

After applying these filters, the data drops to having 97,432 credit events observations for 1780 unique firms. Table A.1 in the appendix shows the number of each type of credit rating event, and the number of unique firms for each year in the sample period. The number of events and firms is limited before 2008. So, we focus our analysis for the period from 2009 onward. The final sample is a panel data-set with 2520 unique, listed firms, covering 62 different credit instruments, with 90,285 credit events spread over 11 years from 2009 to 2020. On average, we have about 36 credit events per firm.

The data-set for our analysis contains the following variables:

1. Firm name
2. Incorporation year
3. Ownership group (if the firm is government owned, associated with a business house or other)
4. Industry classification as per CMIE
5. Industry classification as per the NIC³ code
6. Credit instrument
7. Rating agency
8. Rating given after the credit event
9. Date of the credit event
10. Rating amount

In addition to this, we use the market price observed for the firms to calculate Δ DtD over different periods of time, as described in the following.

³National Industrial Classification-2008

Distance-to-default (DtD)

A limited liability firm with common equity of E defaults on its debt D at maturity if the market value of the firm asset A is lower than D . Merton (1974) modeled E as a call option on the underlying assets A , with the value of E calculated using the Black–Scholes option pricing model. For listed firms, E and its volatility σ_E is obtained from market prices. An estimate of A and σ_A of the firm is then obtained by solving the equations for E and σ_E , either simultaneously or with iterative procedures.⁴

With these estimated values we are able to calculate how far the firm is away from default using the DtD which is defined as the number of standard deviations that A is away from D , or $DtD = \frac{A-D}{\sigma_A A}$.

For each firm in the sample, we calculate a time series of the daily values of DtD for the firm using the daily market prices. The data used in these estimations includes:

1. Market capitalisation of the firm (E): calculated as the product of the closing price of the firm equity as traded at the *National Stock Exchange of India* (NSE) or *Bombay Stock Exchange* (BSE) and the shares outstanding.
2. Equity volatility (σ_E): calculated daily on a rolling basis as the standard deviation of daily returns over the past year (252 days).
3. Risk-free interest rate (r): calculated from the one-year Government of India treasury bill prices.⁵
4. Threshold debt level (D): calculated from the firm's balance sheet as the sum of short-term liabilities and half of the long-term liabilities. This is the definition used in the seminal KMV model (Crosbie and Bohn (2003)). For the purpose of the analysis, we assume that the liabilities for the firm remains the same for the financial year.⁶
5. Maturity of debt, T : calculated as of one year, following standard practice in the credit rating industry.

4 Event study analysis and results

Event studies are a well developed approach to study the impact of corporate announcements on equity returns Brown and Warner (1985). In our analysis, the event studied is either a downgrade ($\Delta CR < 0$) or a re-affirmation ($\Delta CR = 0$). We analyse what is the ΔDtD that takes place before the *event* of a rating change, and what is ΔDtD for the same period of time after the event. A significant and negative value of ΔDtD before a rating downgrade will imply that the DtD leads the credit rating agency. On the other hand, if

⁴Details of the methodology can be seen in Hillegeist et al. (2004) and Vassalou and Yuhang (2004).

⁵The data is available from the *Fixed Income Money Market and Derivatives Association* (FIMMDA) website. <http://www.fimmda.org>

⁶In India, the financial year spans from 1st April to 31st March of the following year.

$\Delta \text{DtD} = 0$ before the event and $\Delta \text{DtD} \neq 0$ after, this will suggest that credit rating leads the market.

The event of the rating change is taken as $t = 0$. We study the impact of this event over an *event window* of 360 days before and after this date.

We consider all the rating events that are the downgrade of a firm-instrument (dn), and calculate the daily average value of the DtD on t days before and after the event date as $a\text{DtD}_{dn,t}$ using the following equation:

$$a\text{DtD}_{dn,t} = \frac{1}{N} \sum_{i=1}^N \text{DtD}_{i,t}$$

where, $\text{DtD}_{i,t}$ is the DtD for firm i at time t , and N is the total number of firm-instruments that were downgraded. t spans an event window of -360 days to +360 days (not including the event date) to cover the entire period of the analysis around the event. Similarly, we calculate the average DtD for all events of credit rating reaffirmations (re) as follows:

$$a\text{DtD}_{re,t} = \frac{1}{m} \sum_{i=1}^m \text{DtD}_{i,t}$$

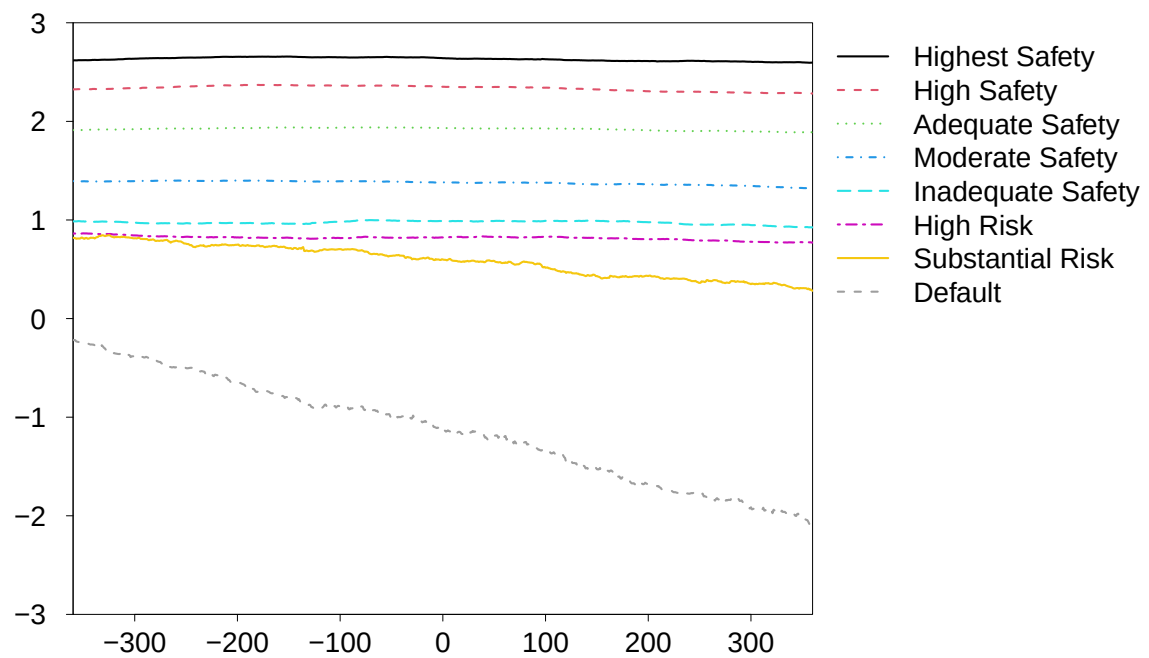
where $\text{DtD}_{i,t}$ is the DtD for firm i , m is the total number of firm-instrument that got reaffirmed, and t goes from -360 days to +360 days around the event date.

Two limitations of the credit events data-set are that (1) we only observe the final ratings which are assigned after the credit event, and (2) the ratings are not standardized across rating agencies for various rated instruments. As a consequence, there are more than 60 rated instruments published by seven rating agencies. One approach to address this problem is to use the CMIE credit risk rating classifications where all firm-instruments are classified as “highest safety”, “high safety”, “adequate safety”, “moderate safety”, “inadequate safety”, “high risk”, “substantial risk”, and “default”. Thus, in our data, we have two sets of ratings for each firm-instrument – that by the original rating agency (does not allow for direct comparison across firm-instruments) and that by CMIE (which allows comparison). For our analysis, we use the CMIE categorisation.

Figure 1 shows the average DtD level for all firm-instruments which were reaffirmed on the event date.

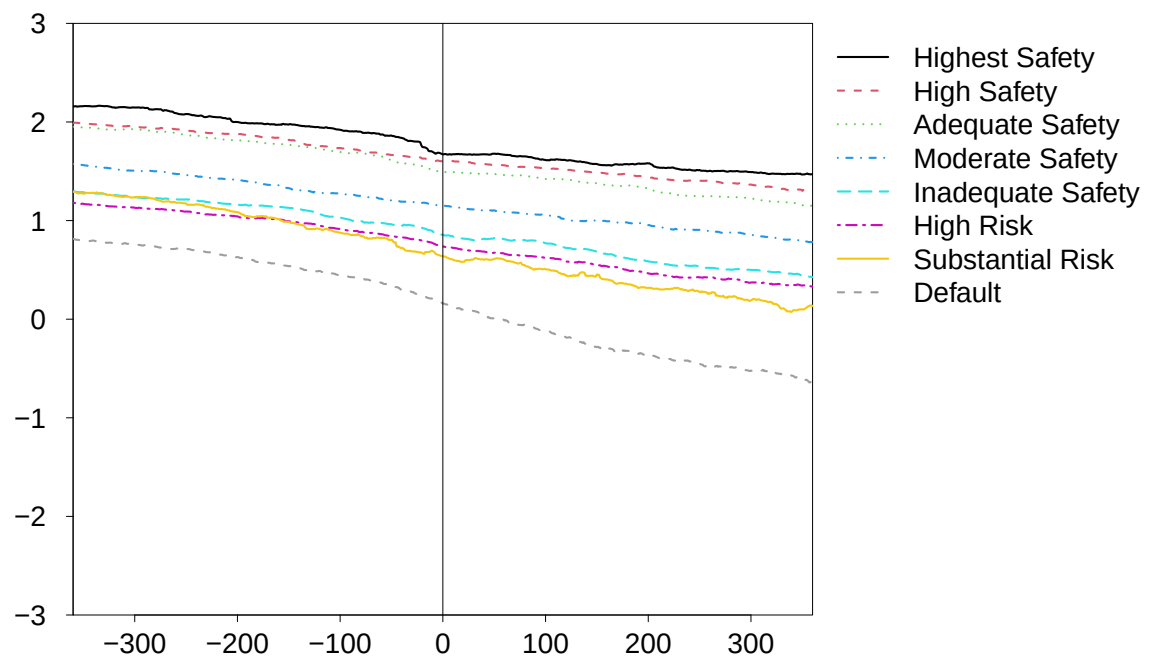
Our first observation is that the average DtD across different risk categories are distinct. Higher risk categories have lower average DtD while the categories of firm-instruments rated in lower risk categories have higher levels of average DtD. Our second observation is that there is no change in the average DtD for most of the categories, except for those instruments which are rated as having substantial risk or are defaulted. For these categories, the average DtD shows a drop in average DtD, both before and after the rating was re-affirmed. The credit information acts to validate the continuing problems of poor financial health of the rated firm instruments.

Figure 1 Average DtD for reaffirmations



We next examine the average DtD for all firm instruments that are downgraded to a particular risk category in Figure 2.

Figure 2 Average DtD for downgrades



In the event of rating downgrades, there are similar observations on the links between the DtD and the credit ratings. Higher the rating classification (lower probability of default), higher the DtD (lower probability of default) of the firm-instrument. This indicates a positive correlation between these two estimates of credit risk.

The changes in the levels show a different story about the responsiveness of each measure to changes in the firm financial health. There is a persistent drop in average DtD across all risk categories prior to the rating downgrade. This suggests that there is market information about deterioration in the financial health of a firm before the rating agency downgrades the firm-instrument. We also observe that the average DtD continues to drop even after the downgrade, an observation which also holds across risk categories. This suggests that the rating downgrade also contributes information about the financial health of the firm into the securities market information.

5 Empirical estimation and results

Our primary focus is on rating downgrades of firm instruments, and whether DtD changes can predict these. Therefore, we use logit models to estimate the magnitude of the signals from the market about changing firm fragility, since the variable of interest Y_i is defined as 1 if there is a rating downgrade for the credit instrument of firm i , and 0 if the rating is reaffirmed. If these estimates are statistically significant, then we can say that changes in DtD at different intervals can be used to predict a rating downgrade. We start with a specification involving only changes in DtD as the explanatory variable horizons with the following model:

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

where,

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

ϕ represents the cumulative logistic distribution, and $\Delta DtD_{i,-N}$ represents the change in DtD $-N$ days before the rating change date. Thus, $\Delta DtD_{i,-1m}$ implies change in DtD of firm i over one month (m) prior to the day of rating change.

We use daily data to estimate the model at four different values of N , where $N = -1m, -3m, -6m, -12m$ (which is one month, three months, six months, and 12 months prior to the date of a rating change). The logit model estimates the unconditional probability of a downgrade at a pre-specified future point in time (three months ahead, six months ahead, etc.). Significant and negative coefficients of the lagged market indicators would support the use of DtD as the lead indicator of firm fragility.

Table 1 presents the estimates of the logit regressions of rating downgrades using the change in DtD over different lead times as the lead indicator. This finds that the estimated coefficients are significant at the 1% level for the all the lead times – 1, 3, 6, and 12 months prior to the rating downgrade. These findings support the claim that changes in DtD have predictive properties. A drop in DtD increases the unconditional likelihood of a downgrade up to 12 months in advance.

Table 1 Logit estimation: ΔDtD as lead indicator

Notes: The table reports the logit results for DtD changes over horizons over 1 month, 3 months, 6 months and 12 months. The values in parentheses are standard errors.

	<i>Dependent variable: Rating downgrades</i>			
	(1)	(2)	(3)	(4)
ΔDtD_{-1m}	–1.158*** (0.047)			
ΔDtD_{-3m}		–0.868*** (0.025)		
ΔDtD_{-6m}			–0.760*** (0.018)	
ΔDtD_{-12m}				–0.593*** (0.012)
Constant	–1.704*** (0.011)	–1.733*** (0.011)	–1.775*** (0.011)	–1.811*** (0.011)
Observations	71,619	71,362	70,952	69,851
Log Likelihood	–31,128.440	–30,731.330	–30,175.550	–29,243.880
Akaike Inf. Crit.	62,260.880	61,466.660	60,355.100	58,491.760
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01			

The coefficients associated with ΔDtD over all horizons are negative, which is consistent with the expected relationship between changes in DtD and ratings. A decreasing value of DtD (closer to zero) implies that the firm’s credit quality has worsened. This, in turn, implies an increase in the probability of a downgrade. When we compare the magnitude of the coefficients on ΔDtD of the most recent period, compared to the coefficient on longer period changes, we find that the most recent period change matters far more to explain the probability of a rating downgrade. These results are in line with [Gropp et al. \(2006\)](#) where they analyze the ability of DtD to signal bank fragility for European banks, and find the DtD to be a leading indicator with a lead time of 6-18 months.

We test which interval has the most impact on predicting changes in credit ratings. For this, we shift to using a set of ΔDtD variables where the changes are calculated over non-overlapping horizons using the following specification:

$$Pr(Y_i = 1) = \phi(\beta_0 + \beta_1 \Delta DtD_{i,-1m} + \beta_2 \Delta DtD_{i,-(3m-1m)} + \beta_3 \Delta DtD_{i,-(6m-3m)} + \beta_4 \Delta DtD_{i,-(12m-6m)}) \quad (1)$$

Here, $\Delta DtD_{i, -(3m-1m)}$ represents the change in DtD between the three months prior, and the DtD one month prior to 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 determine the horizon at which changes in DtD predict the changes in rating best.

Table 2 presents the logit estimates for non-overlapping, prior period DtD changes. The signs on the coefficients over all horizons are negative. This is consistent with the hypothesis about the information of deteriorating financial health measured by the drop in DtD. Additionally, all the prior period DtD changes are statistically significant in explaining the probability of a downgrade. Further, we see that the more recent prior period changes in DtD have significantly higher values than changes in the older prior period changes. These findings are consistent for standalone non-overlapping periods, and all non-overlapping periods taken together.

Table 2 Logit estimation: Identifying the horizon

	<i>Dependent variable: Rating downgrades</i>				
	(1)	(2)	(3)	(4)	(5)
ΔDtD_{-1m}	-1.158*** (0.047)				-0.793*** (0.049)
ΔDtD_{1m-3m}		-0.942*** (0.035)			-0.709*** (0.036)
ΔDtD_{3m-6m}			-0.822*** (0.027)		-0.605*** (0.029)
ΔDtD_{6m-12m}				-0.625*** (0.020)	-0.501*** (0.020)
Constant	-1.704*** (0.011)	-1.705*** (0.011)	-1.717*** (0.011)	-1.724*** (0.011)	-1.807*** (0.011)
Observations	71,619	71,362	70,952	69,851	69,830
Log Likelihood	-31,128.440	-30,944.410	-30,655.340	-29,961.510	-29,308.460
Akaike Inf. Crit.	62,260.880	61,892.810	61,314.690	59,927.010	58,626.920
Note:	*p<0.1; **p<0.05; ***p<0.01				

Since our analysis is done using the firm-instrument level observations, it can be argued that the results are driven by firms that have issued multiple credit instruments. Firms with better financial conditions are likely to have better access to the debt market, and to issue more debt instruments more frequently, on average. In this case, our results will be driven by a limited number of firms in a poor financial conditions not well represented in the data-set.

In order to take this into account, we run the same regression specifications to account for this by adjusting for unique firm-level observations. By unique, we mean that if multiple instruments of a particular firm are downgraded or reaffirmed on the same date, we consider this a unique observation in the data-set. We find that there is approximately 70%

reduction in the number of observations. The sample size drops from roughly 70,000 firm-instrument observations to around 20,000 firm-level observations. This suggests that most of the firm's instruments are reassessed on the same date and reaffirmed or downgraded together. Table 3 documents the estimation results once this adjustment is made to the sample data.

Table 3 Logit estimation: Using unique firm-level observations

I: Logit model over different horizons					
	Dependent variable: Rating downgrades				
	(1)	(2)	(3)	(4)	
ΔDtD_{-1m}	-1.044*** (0.092)				
ΔDtD_{-3m}		-0.823*** (0.049)			
ΔDtD_{-6m}			-0.686*** (0.034)		
ΔDtD_{-12m}				-0.554*** (0.023)	
Constant	-1.625*** (0.019)	-1.651*** (0.019)	-1.682*** (0.020)	-1.716*** (0.020)	
Observations	20,884	20,796	20,659	20,290	
Log Likelihood	-9,413.813	-9,301.944	-9,159.196	-8,869.282	
Akaike Inf. Crit.	18,831.630	18,607.890	18,322.390	17,742.560	
II: Logit model over non-overlapping horizons					
	Dependent variable: Rating downgrades				
	(1)	(2)	(3)	(4)	(5)
ΔDtD_{-1m}	-1.065*** (0.088)				-0.752*** (0.090)
ΔDtD_{1m-3m}		-0.893*** (0.064)			-0.681*** (0.066)
ΔDtD_{3m-6m}			-0.722*** (0.050)		-0.512*** (0.053)
ΔDtD_{6m-12m}				-0.606*** (0.036)	-0.502*** (0.037)
Constant	-1.621*** (0.019)	-1.626*** (0.019)	-1.633*** (0.019)	-1.643*** (0.019)	-1.713*** (0.020)
Observations	20,947	20,859	20,720	20,351	20,348
Log Likelihood	-9,465.161	-9,402.324	-9,323.942	-9,083.127	-8,922.542
Akaike Inf. Crit.	18,934.320	18,808.650	18,651.880	18,170.250	17,855.080
Note:			*p<0.1; **p<0.05; ***p<0.01		

Qualitatively, our results are consistent, even though the magnitude of our estimates comes down slightly for all horizons. We still find standalone changes in DtD for all overlapping and non-overlapping periods to be statistically significant.

6 Robustness tests

6.1 Firm characteristics

In order to control for heterogeneity in firm characteristics, we control for size, age, and industry. Here, we proxy size by the log of total assets. We find the coefficient of size and age are negative and statistically significant at the 0.01 level. These results are consistent with rating agencies providing higher ratings to instruments issued by large and old firms (see Table 4 - model 2, 3 & 4). Furthermore, despite these controls, we still find the coefficient on changes in DtD to be negative and statistically significant below the 0.01 level. These results further support that changes in DtD are relevant in a forecasting rating downgrade.

Table 4 Controlling for firm, rating instrument and CRA specific characteristics

Dependent variable: Rating downgrades								
	Baseline	+ Firm characteristics			+ Rating instrument characteristics			+ Year FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔDtD_{-1m}	-0.793*** (0.049)	-0.882*** (0.054)	-0.880*** (0.054)	-0.794*** (0.055)	-0.789*** (0.056)	-0.785*** (0.056)	-0.734*** (0.056)	-0.759*** (0.057)
ΔDtD_{1m-3m}	-0.709*** (0.036)	-0.850*** (0.041)	-0.850*** (0.041)	-0.759*** (0.042)	-0.767*** (0.042)	-0.748*** (0.042)	-0.728*** (0.042)	-0.784*** (0.043)
ΔDtD_{3m-6m}	-0.605*** (0.029)	-0.660*** (0.034)	-0.656*** (0.034)	-0.615*** (0.034)	-0.612*** (0.034)	-0.607*** (0.035)	-0.609*** (0.035)	-0.624*** (0.036)
ΔDtD_{6m-12m}	-0.501*** (0.020)	-0.565*** (0.023)	-0.563*** (0.023)	-0.529*** (0.023)	-0.531*** (0.024)	-0.517*** (0.024)	-0.504*** (0.024)	-0.450*** (0.025)
size		-0.131*** (0.006)	-0.122*** (0.006)	-0.104*** (0.007)	-0.106*** (0.008)	-0.114*** (0.008)	-0.123*** (0.008)	-0.127*** (0.009)
age			-0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Rating amount					0.00000* (0.00000)	0.00000** (0.00000)	0.00000** (0.00000)	0.00000** (0.00000)
Industry				Y	Y	Y	Y	Y
Instrument						Y	Y	Y
Rating agency							Y	Y
Year								Y
Observations	67,336	67,336	67,336	67,336	66,608	66,608	66,608	66,608
Log Likelihood	-27,473.500	-27,175.880	-27,116.970	-25,666.780	-25,411.540	-25,025.440	-24,770.730	-24,412.050
Akaike Inf. Crit.	54,957.000	54,363.760	54,247.930	51,627.550	51,119.080	50,464.880	49,967.460	49,274.100

Note:

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

6.2 Rating instruments characteristics

The decision to downgrade depends on how market participants perceive various credit instruments. Negative information regarding the financial health of a firm might not affect the rating of a small value debt issued in the past. However, it might lead to a thorough assessment of high-value issuance. Similarly, the maturity profile-short, medium, or long-term of rating instrument-may influence the decision to downgrade differently. To account for these, we re-estimate Eq(1) with two additional instrument-level variables: (1) rating amount; and (2) instrument type. We find the coefficient of rating amount to be positive and statistically significant at the 10% level suggesting high-value issuance

being rated favorably (see Table 4 - model 5 & 6). The changes in DtD also remain statistically significant.

6.3 Differences across CRAs

Differences across CRAs could also impact the quality of risk assessment, which could bias our primary findings. Credit rating in India is highly fragmented. For instance, Table 5 shows that there are seven major CRAs in the Prowess data-set. The average number of clients per CRA is much smaller than the large, diverse client bases of the top three-CRISIL, ICRA, and CARE. Also, different CRAs might be specialized in rating different rating instruments. Therefore, we use CRA fixed-effect to control the rating quality if there are systematic differences across CRAs.

Table 5 Controlling for ratings by credit rating agencies

Rating agency	Downgraded	Reaffirmed	Upgraded	Total	% Total	# of unique firms
ACUITE	26.04	64.76	9.20	2097	2.15	123
BRICKWORK	25.07	61.00	13.93	3395	3.48	364
CARE	18.49	71.52	10.00	21665	22.24	1193
CRISIL	10.41	82.13	7.46	42677	43.80	1434
ICRA	14.69	73.91	11.40	20866	21.42	1020
IND-RA	17.42	71.54	11.04	6649	6.82	478
IVR	30.12	60.24	9.64	83	0.09	23

Therefore, we re-estimate the equation (1) with CRA's fixed-effect to control for unobserved heterogeneity in the credit quality of different rating agencies. Table 4 present the results. As shown in columns (7), our results are equally stronger in this augmented analysis, thus reinforcing the robustness of our findings to control for the quality of the firm's rating agency. We also estimate equation (1) with sub-samples of firms rated by the individual CRAs and find similar results. We have not shown the results to save space, but they are available upon request. We also control for the macroeconomic environment using year fixed effects (column (8) - Table 4). Our findings remain robust to these different specifications.

6.4 Accounting ratios

Since DtD competes with accounting ratios to estimate firm fragility, we tried to control for the firm's latest available accounting ratios in an alternate specification. Following Blöchliger and Leippold (2018), we consider all accounting ratios used in Altman (1968) and Altman et al. (1977) to figure out the list of relevant accounting-based variables. Altman (1968) z-score model considers five financial ratios, while Altman et al.

(1977) ζ -score model considers seven accounting ratios. Since some accounting variables are common in both specifications, we consider only the unique variables. Also, a few of the variables (e.g., leverage) considered by Altman is input in Merton's model. We avoid repetition and do not consider input variables in Merton's model as a separate regressor. The comprehensive list of all accounting-based variables considered is as follows.

- R1 : Liquidity ratio. The ratio is computed as the current assets minus current liabilities divided by total assets.
- R2 : Profitability ratio. This is measured as the ratio of retained earnings to total assets.
- R3 : Productivity ratio. The ratio is calculated as earnings before interest and taxes (EBIT) divided by total assets.
- R4 : Asset utilization. This is measured as the ratio of sales to total assets.
- R5 : Interest coverage ratio. It measures the debt service capability of a firm and is computed as the EBIT divided by total interest payments.
- R6 : Liquidity. This is measured as the ratio of current assets to current liabilities.

Table 6 shows our findings. We find the last available liquidity ratio, profitability ratio, asset utilization ratio, and liquidity ratio statistically significant. Interestingly, the coefficient of the near month change in DtD drops significantly, though it is still significant at the 5% level. Collectively, these results reinforce the robustness of our main findings in controlling for the quality of firms' last available financial statements.

6.5 Additional checks

We perform other additional robustness checks:

1. Split the data based on various other firm and instrument characteristics and test if long-term, short-term, and promise to borrowing instruments are affected differently by the past changes in DtD.
2. Examine at the effect of change in DtD on investment and non-investment grade instruments separately (details in Section B).
3. Introduce a new variable to control the ownership of firms. This is particularly relevant for emerging markets where there tends to be a significant number of firms where the government and business groups have a large shareholding (details in Section C).

Across all these specifications, where we control for instrument type, ownership, and other accounting variables, we find that the change in DtD remains a robust and significant predictor of a credit rating downgrade.

Table 6 Controlling for firm characteristics and accounting variables

	Dependent variable: Rating downgrade				
	Baseline (1)	+ Firm char. (2)	+ Accounting ratios (3)	+ Year FE (4)	+ Rating inst. char. (5)
ΔDtD_{-1m}	-0.793*** (0.049)	-0.794*** (0.055)	-0.320*** (0.110)	-0.285** (0.111)	-0.272** (0.111)
ΔDtD_{1m-3m}	-0.709*** (0.036)	-0.759*** (0.042)	-0.611*** (0.075)	-0.639*** (0.077)	-0.649*** (0.077)
ΔDtD_{3m-6m}	-0.605*** (0.029)	-0.615*** (0.034)	-0.550*** (0.059)	-0.536*** (0.061)	-0.532*** (0.062)
ΔDtD_{6m-12m}	-0.501*** (0.020)	-0.529*** (0.023)	-0.517*** (0.040)	-0.429*** (0.042)	-0.434*** (0.042)
size		-0.104*** (0.007)	-0.191*** (0.014)	-0.195*** (0.015)	-0.197*** (0.016)
age		-0.004*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.008*** (0.001)
Liquidity ratio			0.864*** (0.223)	0.931*** (0.225)	0.933*** (0.226)
Profitability ratio			-21.088*** (1.447)	-20.374*** (1.477)	-19.991*** (1.489)
Productivity ratio			2.088** (0.888)	1.466 (0.908)	1.264 (0.919)
Asset utilization ratio			-0.722*** (0.047)	-0.708*** (0.048)	-0.678*** (0.048)
Interest coverage ratio			-0.011*** (0.002)	-0.011*** (0.002)	-0.009*** (0.002)
Liquidity			-0.247*** (0.043)	-0.261*** (0.044)	-0.261*** (0.043)
Rating amount					-0.00000 (0.00000)
Industry		Y	Y	Y	Y
Year				Y	Y
Instrument					Y
Rating agency					Y

Note:

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

7 Testing model prediction performance

A key potential benefit to evaluate higher frequency market data to predicting credit rating change is it's use as early warnings of an increase in firm fragility to regulators and supervisors. We set up a framework to assess the ability of these models to predict rating changes by using the standard approach of calculating and reporting the estimated model classification errors (types I and II). We follow convention and define type I errors as missed downgrades (i.e., the indicator classifies “no downgrade” when the firm instrument is downgraded) and type II errors as mis-classified non-downgrades (i.e., the indicator classified “downgrade” when the firm-instrument is not downgraded).

From the previous section on estimation results, we use the following four models to examine the classification accuracy:

1. with only ΔDtD as an explanatory variable (baseline model in Table 4);
2. with ΔDtD and firm characteristics – size, age, and industry (such as Model (4) in Table 4);
3. adding rated instruments characteristics – rating amount, rating instrument and rating agency (such as Model (7) in Table 4); and
4. adding the most recently available accounting-based risk ratios that are used in the accounting ratios models of default probability (such as Model (5) in Table 6).

The accuracy of these four models is calculated both using the “Area under the Curve” (AUC) and the Classification Accuracy. These are presented in Table 7. The misclassification of predictions by the models – Type I and Type II errors – are presented in Table 8.

Table 7 Model performance when using ΔDtD as a predictor of increased rating changes

Model	Specification	Area under the curve (AUC)	Classification Accuracy
1	ΔDtD only	0.62	0.88
2	ΔDtD + Firm char.	0.75	0.88
3	ΔDtD + Firm char. + Rated instrument char.	0.77	0.89
4	ΔDtD + Firm char. + Rated instrument char. + Accounting ratios	0.81	0.89

With only ΔDtD as the independent variable, the overall classification accuracy is 0.88, with the area under the receiver operating characteristics curve (AUC) of 0.62. The addition of the firm characteristics-size, age, and industry significantly improves the explanatory and predictive power with AUC increasing to 0.75. When we add rating instrument characteristics (rating amount, rating instrument, and rating agency) this increases marginally to 0.77. The final AUC where we add the accounting ratios that are traditionally used to estimate the default probability of the firm, the AUC shows a larger improvement to 0.81.

This indicates that these models can be used by risk evaluation departments of financial investment firms and that of financial sector regulators as a mechanism to monitor what are likely to be the number and magnitude of rating downgrades of the instruments held in the portfolio of investment firms. Taken as a whole, it could provide an early indicator of increasing financial fragility across the financial investment sector.

However, these results must be considered with more nuanced understanding of the model prediction performance, in the form of the “Confusion matrix”. This is a classification matrix which presents the Type I and Type II error classification for the different models in Table 8. We see that a possible reason for the high values of the prediction performance in Table 7 is mainly driven by the correct classification of rating reaffirmations. In most rating change data-sets, the number of rating downgrades is significantly smaller than the number of rating reaffirmations. In our data, it is around 12%. This

means that even a random guess of reaffirmation will be recorded as a highly accurate prediction for a rating change.

Table 8 Model performance using Type I and Type II errors of prediction

Predicted	Actual							
	Model 1		Model 2		Model 3		Model 4	
	0	1	0	1	0	1	0	1
Reaffirmed (0)	37951	4985	37788	4761	37740	4638	37669	4428
Downgraded (1)	45	120	208	344	256	467	327	677

A closer examination of Type I errors (missed downgrades) finds that only in 120 out of 5105 cases is the model able to correctly predict a rating downgrade. In the best performing model, a downgrade can be predicted in 677 out of 5105 cases. This is a considerable improvement when compared with only ΔDtD as the explanatory variable. However, this increase in accuracy comes at a cost, with Type II errors increasing from 45 mis-classified non-downgrades to 327.

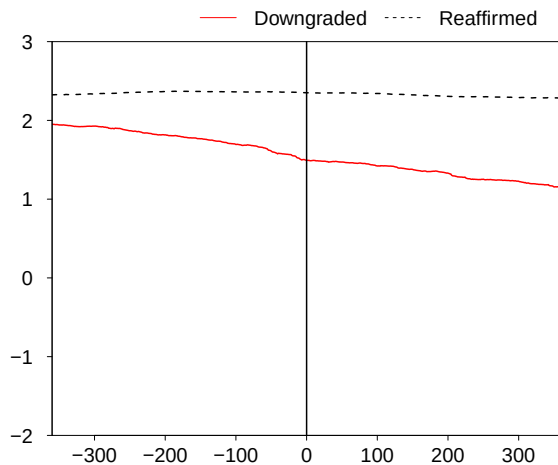
An important piece of information missing in our data-set is what the credit rating was before the rating change event date. In the rating reaffirmations of Figure 1, the magnitude of the drop in DtD around a rating change varies for different risk categories. We conjecture that if the models were controlled for the risk classification of the firm before the rating changed, the model accuracy would have been higher.

Figure 3 presents the average DtD of downgraded firms with the average DtD of reaffirmed firms ± 360 days around the event date in the same risk category as the CMIE risk classification. The solid red lines represent the average DtD of firms with a higher rating before the downgrade, while the dotted black lines represent the average DtD of firms reaffirmed in that risk category. Since a firm can not be downgraded to the highest safety category and can not be downgraded below default, we exclude these two categories from the graph. We see very different changes in DtD for different risk categories of the firm instruments that are downgraded. If we use credit rating of the firm instrument before the rating change, we may be able to control for the initial risk level and the expected drop required for rating transition.

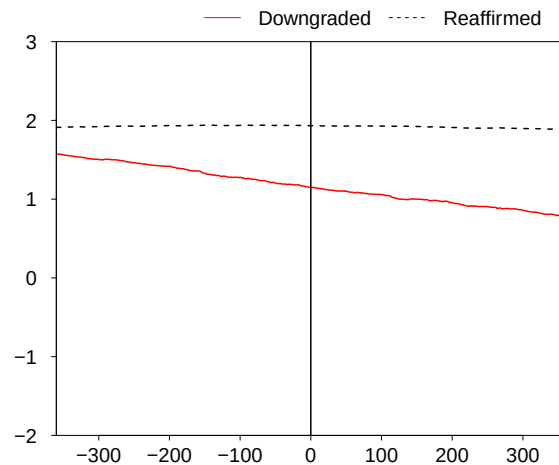
Figure 3 Δ DtD across different risk categories

The graphs show the average DtD of downgraded firms with the average DtD of reaffirmed firms $\pm$ 360 days around the event date in the same risk category as per the CMIE risk classification. The solid red lines represent the average DtD of firms with a higher rating before the downgrade, while the dotted black lines represent the average DtD of firms reaffirmed in that risk category. Since a firm can not be downgraded to the highest safety category and can not be downgraded below default, these two risk categories are excluded.

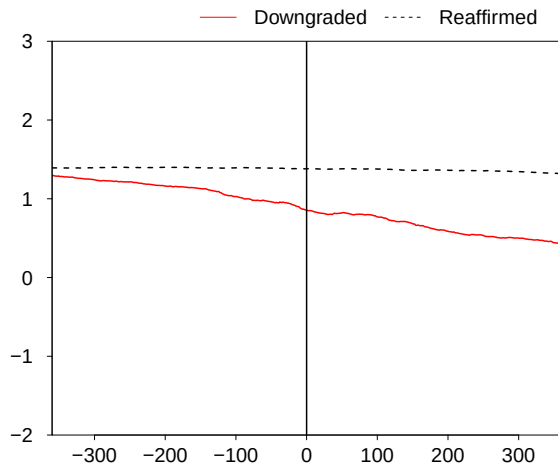
(a) Highly safe



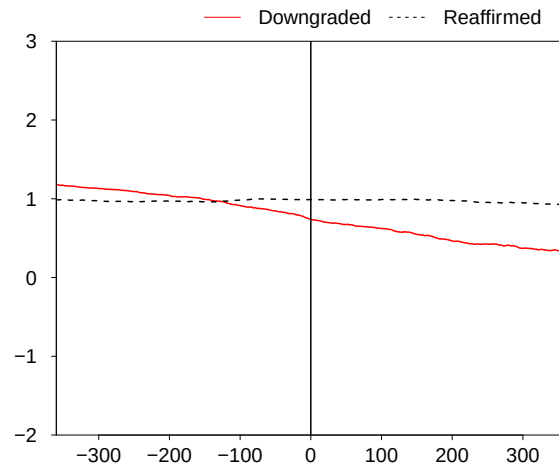
(b) Adequately safe



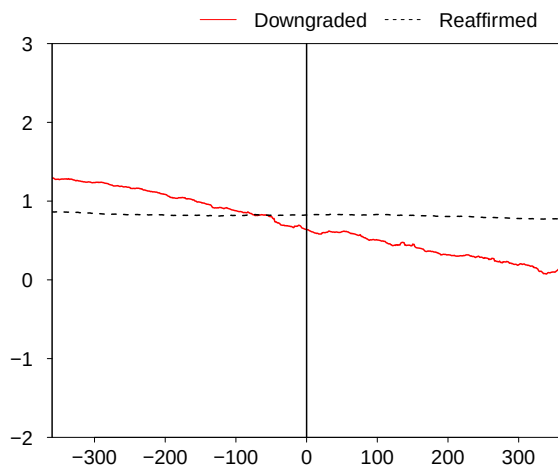
(c) Moderately safe



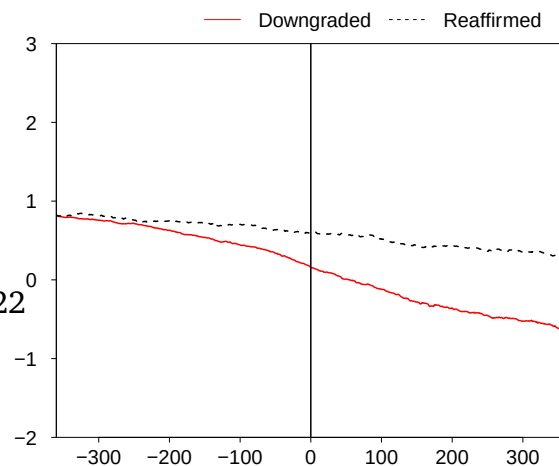
(d) Inadequately safe



(e) High risk



(f) Substantial risk



8 Conclusion

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

Given this continued dependence on 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 using ratings in the fund management industry today. We use data on credit ratings, market price information, firm characteristics, and accounting ratios for listed firms to figure if changes in the more frequently observed market-based distance to default (DtD) measures can be used to indicate changes in the credit rating?

A non-parametric event study of the levels of average DtD in a one year period before, and one year after credit rating downgrades, find that the DtD can indicate information about the financial health of a firm. much before the rating agencies update credit ratings. Our findings are that firms classified in a given rating category have a corresponding level of average DtD. Higher credit rating category firms have higher DtD levels. More importantly, we find that the average DtD level of all the rating categories drop persistently for downgraded firms with a lead time between 1 to 12 months.

Logistic regression estimates suggest that previous period changes in DtD (from 1 month to 12 months in the past) significantly capture information about the deterioration in the financial health of a firm, as measured by a rating downgrade. In addition, firm characteristics, rating instrument characteristics, as well as the traditional firm accounting ratios used to predict the probability of default of a firm contribute significantly to the probability of a drop in the rating of a firm instrument. However, changes in DtD continue to have significant predictive power.

The results of this paper are consistent with earlier studies that find that market and accounting measures can predict the probability of decreasing financial health of a firm. What is new in this paper 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 become even more critical during periods of market crisis, and can prove very useful for fund managers with debt investments in their portfolio.

References

- Agarwal, V., Taffler, R., 2008. Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking & Finance* 32, 1541–1551.
- Altman, E., Katz, S., 1976. Statistical bond rating classification using financial and accounting data, in M. Schiff and G. Sorter (eds) *Topical Research in Accounting*. NYU press.
- Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23, 589–609.
- Altman, E.I., Haldeman, R.G., Narayanan, P., 1977. ZETA analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance* 1, 29–54.
- Bharath, S.T., Shumway, T., 2008. Forecasting default with the merton distance to default model. *Review of Financial Studies* 21, 1339–1369.
- Blöchlinger, A., Leippold, M., 2018. Are ratings the worst form of credit assessment except for all the others? *Journal of Financial and Quantitative Analysis* 53, 299–334.
- Blume, M., Lim, F., Mackinlay, A., 1998. The declining credit quality of u.s. corporate debt: Myth or reality? *Journal of Finance* 53(4), 1389–1413.
- Brown, S.J., Warner, J.B., 1985. Using daily stock returns: The case of event studies. *Journal of Financial Economics* 14, 3–32.
- Campbell, J., Hilscher, J., Szilagyi, J., 2011. Predicting financial distress and the performance of distressed stocks. *Journal of Investment Management* 9(2), 1–21.
- Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. *The Journal of Finance* 63, 2899–2939.
- Chava, S., Jarrow, R., 2004. Bankruptcy prediction with industry effects. *Review of Finance* 8, 537–539.
- Crosbie, P.J., Bohn, J.R., 2003. Modeling default risk. Moody's KMV .
- Gropp, R., Vesala, J., Vulpers, G., 2006. Equity and bond market signals as leading indicators of bank fragility. *Journal of Money, Credit and Banking* 38, 399–428.
- Hillegeist, S.A., Keating, E., Cram, D.P., Lunsford, K.G., 2004. Assessing the probability of bankruptcy. *Review of Accounting Studies* 9, 5–34.
- Kaplan, R., Urwitz, G., 1979. Statistical models of bond ratings: A methodological inquiry. *Journal of Business* 52, 231–261.

- Kealhofer, S., 2003. Quantifying credit risk i: default prediction. *Financial Analysts Journal* 59, 30–44.
- Merton, R., 1974. On the pricing of corporate debt: the risk structure of interest rates. *Journal of Finance* 29, 449–470.
- Oderda, G., Dacorogna, M., Jung, T., 2003. Credit risk models: do they deliver their promises? a quantitative assessment. *Review of Banking, Finance and Monetary Economics* 32, 177–195.
- Ohlson, J.A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 18, 109–131.
- Shah, A., Thomas, S., 2000. Systemic fragility in Indian banking: Harnessing information from the equity market. Technical Report. URL: https://www.mayin.org/ajayshah/PDFDOCS/ShahThomas2000_depositinsurance.pdf.
- Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business* 74, 101–124.
- Vasicek, O.A., 1984. Credit valuation .
- Vassalou, M., Yuhang, X., 2004. Default risk in equity returns. *Journal of Finance* 59, 831–868.
- White, L.J., 2010. Markets: The credit rating agencies. *Journal of Economic Perspectives* 24, 211–26.
- Zmijewski, M.E., 1984. Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research* , 59–82.

A Credit ratings for the period, 1989-2020

Table A.1 Annual coverage of firms and credit events

Year	Upgraded	Downgraded	Reaffirmed	Total	# of unique firms
1989	1	0	0	1	1
1991	2	0	0	2	2
1992	3	1	0	4	3
1993	2	0	0	2	2
1994	2	7	10	19	18
1995	5	20	2	27	26
1996	42	42	4	88	72
1997	120	87	4	211	138
1998	305	343	13	661	353
1999	225	305	33	563	296
2000	111	393	54	558	268
2001	154	506	16	676	272
2002	97	608	24	729	275
2003	54	475	41	570	240
2004	29	361	60	450	187
2005	19	421	48	488	221
2006	22	499	25	546	241
2007	24	452	15	491	214
2008	207	826	28	1061	266
2009	775	2820	171	3766	723
2010	318	3851	822	4991	1084
2011	675	4622	653	5950	1240
2012	1458	5190	317	6965	1374
2013	1172	4941	634	6747	1354
2014	773	5524	1085	7382	1492
2015	871	5850	1173	7894	1516
2016	1056	6416	943	8415	1592
2017	998	7162	1059	9219	1694
2018	939	7713	982	9634	1768
2019	1905	8453	617	10975	1780
2020	1729	6315	303	8347	1454

B Effect of rated instruments characteristics

In this section, we look at various other characteristics of the rated instruments that are not directly observable in our dataset but might be of relevance. We ask ourselves the following questions: (1) Are short-term instruments more influenced by recent drops in DtD?; (2) Are promises of borrowing instruments less influenced by changes in DtD?; and (3) Are investment grade instruments less influenced by changes in DtD?

To answer these, we split the dataset in multiple ways. First, we classify all rated instruments as long-term, short-term and promise to borrow instruments. Table B.1 shows our classification. We rely on value judgment since we do not have sufficient information to classify all instrument types. Some of the instruments which we are not able to classify, we drop from our analysis. Second, we look at the effect of change in DtD on investment and non-investment grade instruments separately. We do not have the instrument's rating before the credit event date, we consider the rating post-credit event as a proxy for the non-/investment grade. We consider "Highest safety" "High safety," "Adequate safety," and "Moderate safety" as investment grade, while the rest are classified together as non-investment grade.

Our findings suggest that the past changes less influence the rating downgrade of short-term instruments in DtD compared to long-term instruments (Table B.2 - Part I). Also, the near-month changes in DtD lost statistical relevance for short-term instruments. When we look at the promise of borrowing instruments, the results are in-line with short-term instruments, but past changes in DtD show higher coefficients (Table B.2 - Part II). The effect of change in DtD on investment and non-investment grade instruments considered separately suggests that changes in DtD are a more consistent predictor for investment-grade instruments. In all cases, even controlling for instrument type, ownership, and other accounting variables, the changes in DtD remain a robust and significant predictor of a credit rating downgrade.

Table B.1 Maturity classification of rated instruments

Sl. No.	Security Name (in CMIE Prowess)	# of obs.	Long-Short flag
1	Long term Loans	11835	Long-term
2	Cash Credit	10032	Short-term
3	Term loans	9732	Long-term
4	Short-term loan	7832	Short-term
5	Letter Of credit	7665	Promise of borrowing
6	Commercial paper	6455	Short-term
7	Non-fund-based financial facility/instrument	6159	Promise of borrowing
8	Fund based financial facility/instrument	5495	Promise of borrowing
9	Bank Guarantee	5199	Promise of borrowing
10	Fixed rate unsecured non-convertible debentures	5141	Long-term
11	Non-government debt	3823	Long-term
12	Non convertible unsecured debentures/bonds/notes/bills	3774	Not clear
13	Working capital loan	2763	Short-term
14	Fixed deposits (including intercorporate deposits)	1875	Not clear
15	Packing Credit	1498	Short-term
16	Debentures / Bonds / notes / bills	1479	Not clear
17	Non-fund based working capital limit	920	Promise of borrowing
18	Cash	808	Short-term
19	Bill Purchase / Bill Discounting / Bill negotiation	804	Short-term
20	Others	618	Short-term
21	Overdraft	557	Promise of borrowing
22	Line of credit	472	Promise of borrowing
23	Foreign bill purchase / discounting / negotiation	420	Short-term
24	Pass through certificates	269	Short-term
25	Buyer's credit	224	Short-term
26	Forwards	209	Short-term
27	Foreign currency term loan	203	Long-term
28	Fixed rate unsecured partly convertible debentures	201	Long-term
29	Preference shares	177	Long-term
30	Debt	108	Short-term
31	Acquirers/Investors' share/payout in assignment of receivables	106	Short-term
32	Post-shipment credit	89	Short-term
33	Non convertible secured debentures/bonds/notes/bills	79	Not clear
34	Pre-shipment credit	56	Short-term
35	Fixed rate secured non-convertible debentures	40	Long-term
36	Second loss facility - securitisation	37	Not clear
37	Export finance	30	Short-term
38	Derivatives	28	Short-term
39	Factoring	26	Short-term
40	Medium-term loan	22	Long-term
41	Vendor financing	20	Short-term
42	Fixed rate pass through certificate	17	Long-term
43	Cash management bills	16	Short-term
44	Fully convertible unsecured debentures/bonds/notes	16	Not clear
45	Gold	12	Short-term
46	Foreign currency	11	Short-term
47	Non-cumulative preference shares	9	Long-term
48	Mortgage loan	8	Long-term
49	Optionally convertible unsecured debentures/bonds/notes/bills	7	Not clear
50	Partly Convertible unsecured debentures/bonds/notes/bills	7	Short-term
51	Secured premium notes (SPN)	7	Short-term
52	Bills payable	6	Short-term
53	Fixed rate dated securities	6	Long-term
54	Letter of credit discounting	6	Short-term
55	Cumulative convertible preference shares	5	Long-term
56	Deep discount / Zero coupon unsecured non-convertible debentures/bonds/notes/bills	3	Not clear
57	Foreign unsecured fully-convertible bonds	3	Long-term
58	Pre-shipment credit in foreign currency (PCFC)	3	Short-term
59	Floating rate unsecured non-convertible debentures	2	Long-term
60	Secured debentures/ bonds/notes/bills	2	Not clear
61	Treasury bills	2	Short-term
62	Certificate of deposit	1	Long-term
63	Deep discount / Zero coupon secured non-convertible debentures	1	Long-term
64	Deferred purchase consideration	1	Short-term
65	Options	1	Short-term

Table B.2 Effect of various rated instruments characteristics**Part I: Are short-term instruments more influenced by recent drops in DtD?**

	<i>Dependent variable: Rating downgrade</i>					
	Without controls			With controls		
	(All)	(Long-term)	(Short-term)	(All)	(Long-term)	(Short-term)
ΔDtD_{-1m}	-0.793*** (0.049)	-0.618*** (0.081)	-0.767*** (0.093)	-0.220** (0.110)	-0.301* (0.176)	-0.087 (0.204)
ΔDtD_{1m-3m}	-0.709*** (0.036)	-0.715*** (0.058)	-0.676*** (0.066)	-0.620*** (0.077)	-0.721*** (0.125)	-0.466*** (0.142)
ΔDtD_{3m-6m}	-0.605*** (0.029)	-0.530*** (0.047)	-0.615*** (0.053)	-0.533*** (0.061)	-0.523*** (0.097)	-0.597*** (0.114)
ΔDtD_{6m-12m}	-0.501*** (0.020)	-0.463*** (0.033)	-0.530*** (0.038)	-0.435*** (0.042)	-0.373*** (0.067)	-0.498*** (0.078)
Firm characteristics				Y	Y	Y
Instrument characteristics				Y	Y	Y
Year				Y	Y	Y
Accounting ratios				Y	Y	Y
Ownership				Y	Y	Y
Observations	69,830	21,153	23,206	41,675	12,483	14,265
Log Likelihood	-29,308.460	-10,064.580	-8,845.167	-10,053.860	-3,615.469	-3,049.182
Akaike Inf. Crit.	58,626.920	20,139.170	17,700.330	20,453.720	7,572.939	6,440.364

Part II: Are promise of borrowing instruments less influenced by changes in DtD?

	<i>Dependent variable: Rating downgrade</i>		
	(Baseline)	(PoB)	(Rest)
ΔDtD_{-1m}	-0.220** (0.110)	-0.032 (0.218)	-0.250* (0.129)
ΔDtD_{1m-3m}	-0.620*** (0.077)	-0.662*** (0.148)	-0.609*** (0.092)
ΔDtD_{3m-6m}	-0.533*** (0.061)	-0.596*** (0.123)	-0.508*** (0.071)
ΔDtD_{6m-12m}	-0.435*** (0.042)	-0.441*** (0.083)	-0.427*** (0.049)
Firm characteristics	Y	Y	Y
Instrument characteristics	Y	Y	Y
Year	Y	Y	Y
Accounting ratios	Y	Y	Y
Ownership	Y	Y	Y
Observations	41,675	12,087	29,588
Log Likelihood	-10,053.860	-2,815.292	-7,143.469
Akaike Inf. Crit.	20,453.720	5,968.584	14,632.940

Part III: Are investment grade instruments less influenced by changes in DtD?

	<i>Dependent variable: Rating downgrade</i>		
	(Baseline)	(Investment grade only)	(Non-investment grade only)
ΔDtD_{-1m}	-0.220** (0.110)	-0.423*** (0.144)	0.295 (0.180)
ΔDtD_{1m-3m}	-0.620*** (0.077)	-0.727*** (0.101)	-0.478*** (0.130)
ΔDtD_{3m-6m}	-0.533*** (0.061)	-0.572*** (0.080)	-0.369*** (0.102)
ΔDtD_{6m-12m}	-0.435*** (0.042)	-0.552*** (0.053)	-0.109 (0.074)
Firm characteristics	Y	Y	Y
Instrument characteristics	Y	Y	Y
Year	Y	Y	Y
Accounting ratios	Y	Y	Y
Ownership	Y	Y	Y
Observations	41,675	36,126	5,549
Log Likelihood	-10,053.860	-6,427.435	-2,735.299
Akaike Inf. Crit.	20,453.720	13,190.870	5,746.598

Note: *p<0.1; **p<0.05; ***p<0.01

C Effect of government ownership

In this section, we estimate the effect of ownership structure on rating credit downgrades and check if our results are robust to ownership control. Based on the CMIE Prowess owner group code, we first classify firms into five broad categories (see Table C.1): (1) private standalone firms; (2) firms belonging to a business house; (3) foreign firms; (4) government-owned firms;⁷ and (5) other.⁸ When we compare the number of firm-instrument observations across different ownership categories, we found government firms, on average, have 94 credit observations against 46 for business groups. standalone private and foreign firms have, on average, 26 credit observations in our dataset.

Table C.1 Credit events by ownership

	Downgraded	Reaffirmed	Upgraded	Total	% of Total	# of unique firms
Private (Standalone)	16.71	71.20	12.09	38344	39.35	1459
Business Group	14.24	77.53	8.22	50086	51.41	1080
Foreign	8.67	84.76	6.58	2965	3.04	110
Central Govt. - Commercial Enterprises	3.63	93.94	2.43	5266	5.40	56
Central Government - Takenover Enterprises	15.38	84.62	0	26	0.03	1
Central and Private sector	66.67	33.33	0	9	0.01	1
State Govt. - Commercial Enterprises	12.74	80.78	6.48	463	0.48	9
State and Private sector	17.89	73.98	8.13	123	0.13	4
NRI	8.87	75	16.13	124	0.13	2
Joint Sector	0	96.15	3.85	26	0.03	1

However, comparing the instruments downgraded across ownership categories, we find that central government-issued securities are rarely downgraded (or upgraded). Our sample only observed a downgrade in 3.63% of the cases. We also found that instruments issued by foreign firms are downgraded only in 8.67% of the cases. This number rises in the case of State government-issued securities (12.74%) and further for firms owned by business houses (14.24%). The highest firm-instruments downgrade is observed for standalone private firms at 16.71%. The number of issuances by ownership categories and the proportion of downgrades taken together suggest that market access and risk profile are influenced by ownership.

To ensure the robustness of our findings, we re-estimate Eq(1) while controlling for the ownership characteristic of firms. Table C.2 (model 1 and 2) suggest that changes in DtD

⁷We classify "Central Govt. - Commercial Enterprises", "Central Government - Taken over Enterprises", "Central and Private sector", "State and Private sector", and "State Govt. - Commercial Enterprises" as government enterprises.

⁸"NRI" and "Joint Sector" firms are together classified as "other."

are still robust predictors of a rating downgrade. Our results are also robust when we control for additional firm characteristics, rated instrument characteristics, accounting ratios, and year fixed-effect.⁹ While we had not originally set out to estimate the effect of ownership on rating downgrade, our results do suggest that ownership matters. Private standalone firms are more frequently downgraded than business group-owned firms. And both are downgraded way more frequently compared to government-owned firms.

Table C.2 Effect of ownership

Note: we create separate dummy variables for each ownership category. D(.) stands for Dummy. BS char. stands for accounting-based risk variables.

	<i>Dependent variable: Rating downgrade</i>					
	Ownership (1)	+ ΔDtD (2)	+ Firm char. (3)	+ Rating inst. char. (4)	+ BS char. (5)	+ Year (6)
D(Private: Standalone)	0.275*** (0.020)	0.372*** (0.022)	0.176*** (0.030)	0.175*** (0.030)	0.384*** (0.049)	0.413*** (0.050)
D(Government)	-1.813*** (0.088)	-1.729*** (0.090)	-0.987*** (0.106)	-0.915*** (0.110)	-1.296*** (0.228)	-1.231*** (0.228)
D(Foreign)	-0.508*** (0.074)	-0.442*** (0.078)	-0.584*** (0.097)	-0.508*** (0.099)	-0.213 (0.166)	-0.206 (0.168)
D(Other)	-2.987*** (1.000)	-2.828*** (1.003)	-3.163*** (1.009)	-15.262 (246.218)	-16.368 (682.018)	-16.317 (679.541)
ΔDtD _{-1m}		-0.794*** (0.049)	-0.775*** (0.055)	-0.716*** (0.056)	-0.263** (0.110)	-0.227** (0.111)
ΔDtD _{1m-3m}		-0.689*** (0.036)	-0.745*** (0.042)	-0.714*** (0.042)	-0.597*** (0.075)	-0.631*** (0.078)
ΔDtD _{3m-6m}		-0.621*** (0.029)	-0.607*** (0.034)	-0.603*** (0.035)	-0.542*** (0.059)	-0.534*** (0.061)
ΔDtD _{6m-12m}		-0.494*** (0.021)	-0.526*** (0.023)	-0.502*** (0.024)	-0.515*** (0.040)	-0.438*** (0.042)
size			-0.074*** (0.008)	-0.095*** (0.009)	-0.137*** (0.017)	-0.141*** (0.017)
age			-0.002*** (0.001)	-0.002*** (0.001)	-0.007*** (0.001)	-0.006*** (0.001)
Rating amount				0.00000*** (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)
Industry FE			Y	Y	Y	Y
Instrument				Y	Y	Y
Rating agency				Y	Y	Y
Accounting ratios					Y	Y
Year FE						Y
Observations	77,683	69,830	63,528	62,839	41,675	41,675
Log Likelihood	-32,895.150	-28,712.030	-23,820.830	-23,028.260	-10,101.390	-9,965.117
Akaike Inf. Crit.	65,800.300	57,442.060	47,943.650	46,490.530	20,638.790	20,384.230
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01					

⁹Since the "Central government - Taken over enterprises" were private enterprises in the past and were taken over by the government (for reasons related to bankruptcy, nationalization, or employee protection, etc.), as robustness tests, we also analyze by removing "Central Government - Taken over Enterprises." Our results are robust to these alternate specifications.