Rating Efficiency in the Indian Commercial Paper Market

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Abstract:

This memo examines the efficiency of the rating system for commercial paper (CP) issues in India, for issues rated A1+ that constitute over 97 per cent of issues by volume. Even within a single rating category, CP issues by different issuers have a large variation in spread within a month—over 200 basis points from the 10th to the 90th percentile—suggesting significant differences in credit risk across issuers in this market. The market implied probability of default (measured using the Merton's 'Distance to Default') as well as the issuer's long-term ratings, have significant economic and statistical power to explain the spread of CP issues. The baseline results suggest that a non-financial borrower with a long-term rating of AAA has a CP spread that is 85 basis points lower than a non-financial borrower with a long-term rating of A. The corresponding difference between AAA and A rated financial borrowers is 42 basis points. This holds even when the same rating agency rates the long-term debt and the CP issue, implying that differences in rating methodology cannot explain the difference in spreads. Overall, the results suggest that there is scope for improving the informativeness of CP ratings in India by creating finer grades in the A1+ category.

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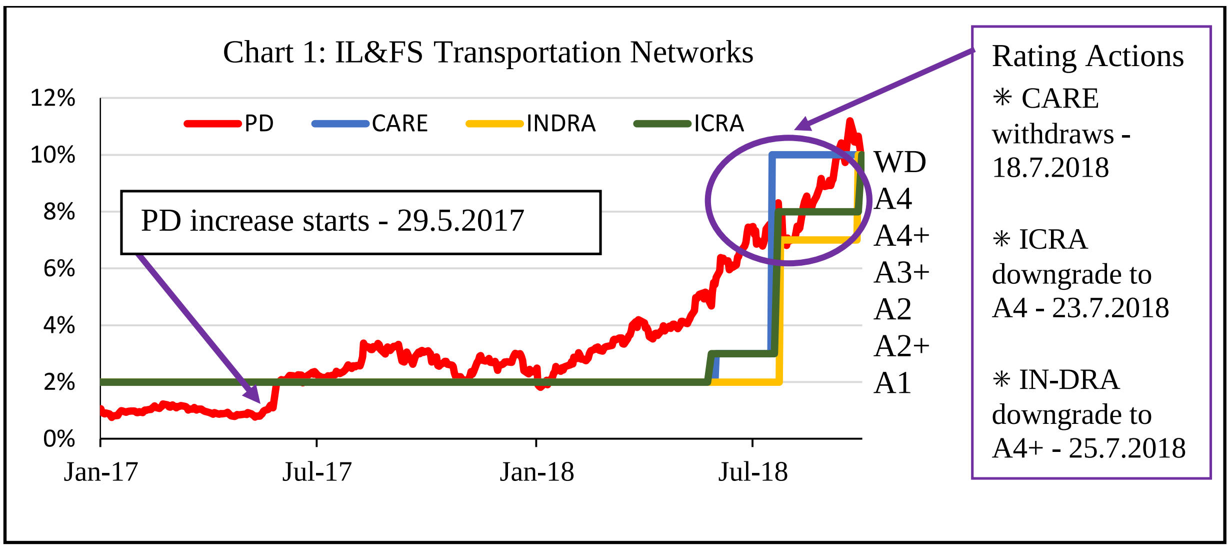
I. Introduction

The default of Infrastructure Leasing and Financial Services Limited (IL&FS) brought to the forefront the role of rating agencies in creating a timely warning system for investors. IL&FS first delayed repayment of an inter-corporate loan for the amount of Rs.450 crore from the Small Industries Development Bank of India (SIDBI) in June 2018.[2] Subsequently, between 12 and 25 September 2018, the company and its subsidiaries defaulted on five bank loans.[3]

Chart 1 shows the market-implied probability of default of IL&FS Transportation Networks Ltd. (a subsidiary of IL&FS). The market-implied default probability had started increasing from 29 May 2017 — suggesting that the debt market had predicted an increased likelihood of default of over one year prior to the first (unreported) default on the SIDBI loan.[4] In contrast to the pattern observed in the probability of default, most rating agencies did not update their ratings until July 2018.



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2 '[Debt and Defaults: What Happened to IL&FS](https://www.moneycontrol.com/news/business/companies/debt-and-defaults-what-happened-to-ilfs-2952381.html)', https://www.moneycontrol.com/news/business/companies/debt-and-defaults-what-happened-to-ilfs-2952381.html.

3 'IL&FS in more trouble: 7 Defaults in last 15 Days; Fails to service yet another short-term deposit today', *Financial Express*. Available at: https://www.financialexpress.com/industry/banking-finance/il-ilfs-fails-to-service-rs-52-43-crore-worth-short-term-deposit-today/1329163/.

4 Downloaded from Bloomberg.

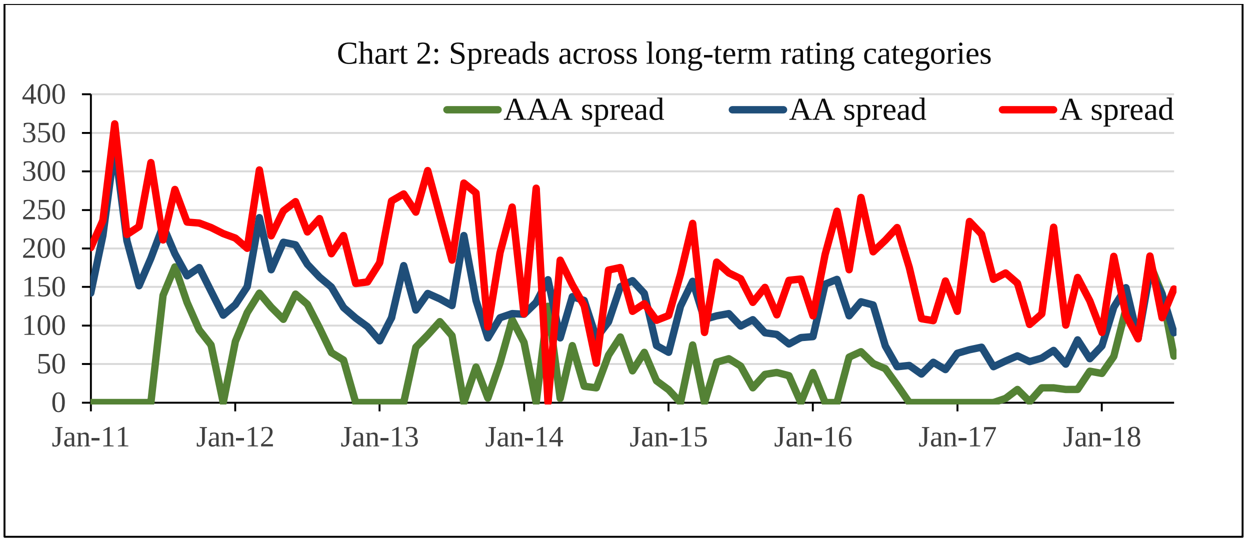
To what extent is the predictability of default of IL&FS generalizable to a larger sample? Do buyers in the commercial paper (CP) market price credit risk appropriately? This memo examines this issue by studying the relationship between proxies for credit risk and CP spreads at issuance. The measures of credit risk used are: (i) Distance to Default (DTD) developed by Merton (1974), which is widely used by rating agencies such as S&P and Moody's in the creation of 'market-implied probability of default', and (ii) long-term ratings of the CP issuing firm.

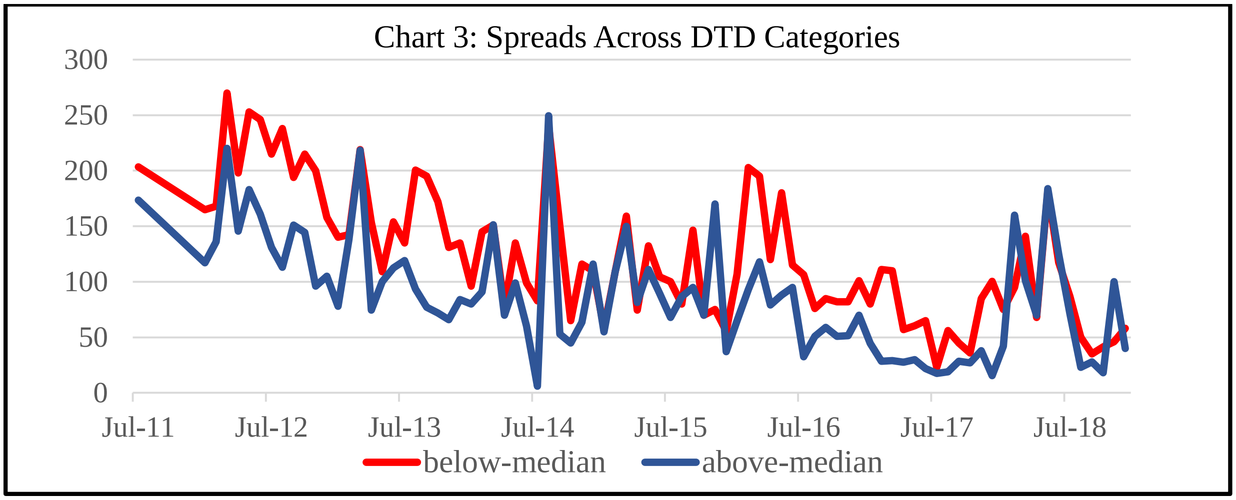
The use of DTD is motivated by the long literature in credit risk that finds that the Merton model performs well in default prediction. In fact, the Credit Risk Initiative at the Risk Management Institute in Singapore estimates probabilities of default for corporations in over 100 countries, and finds that DTD is an extremely valuable early warning indicator of default in all of these countries. The use of long-term ratings is made necessary by the fact that over 97 per cent of commercial paper issues in India are rated A1+. Thus, there is little variation in short-term ratings for CP issues. In contrast, long-term ratings of CP obligors exhibit much more variation which allows for statistical tests on the discriminatory power of ratings on CP spreads.

To evaluate the impact of the above two variables on CP spreads, all CP issues by non-financial firms are segregated by the most recent long-term rating of the borrower prior to the CP issue date. Chart 2 presents the results of the different long-term rating categories from 2011 to 2018. As can be clearly seen, CP spreads for issuers with a long-term rating of AA are significantly above CP spreads for issuers with a long-term rating of AAA. The same effect is observed for issuers with long-term rating of AA versus A. The differences in magnitude are also extremely large—often more than 50 basis points per rating difference.

If the sample is divided into DTD categories, a similar pattern is observed. In the overall sample, CP spreads of non-financial firms with above median DTD are 115 basis points, whereas the spreads for non-financial firms with below median DTD are 80 basis points.[5] Chart 3 splits the sample of non-financial issues by issues with above and below median DTD. In most cases, the spreads for high DTD firms are much lower as predicted by the Merton model. The above provides preliminary evidence that there is significant scope for making the CP issuance categories more granular, as there is a large variation in spreads even within the same CP rating category. Further, this variation has a significant correlation with long-term ratings as well as DTD, both of which are computed by rating agencies on a regular basis.

[5] Note that higher DTD implies lower default risk and vice versa.





Next, an ordinary least squares model is used to examine if the above effects of DTD and long-term ratings are present after controlling for other determinants of CP spreads. In addition to DTD and/or long-term ratings, issue size, maturity, equity ratio, size of the firm, day and industry fixed effects are used as independent variables. The day fixed effects should account for all macroeconomic effects that impact spreads on a daily basis, and the other controls should account for industry and firm-level determinants of credit risk.

Even after use of all of these controls, the baseline regression results imply that a non-financial borrower with an AAA long-term rating has a spread almost 85 basis points lower than a non-financial borrower with an A rating. For financial firms, the corresponding difference between AAA and A rated firms is 42 basis points. DTD also has a highly significant impact on

CP spreads. To the extent that both DTD and long-term ratings are negatively related to CP spreads, this suggests that buyers in the CP market do price default risk.

This continues to hold even when the *same* rating agency has rated the CP issue and provided the long-term rating. Thus, differences in rating methodology across rating agencies cannot account for the additional explanatory power of long-term ratings on CP spreads. These results imply that the market derives significant information from the long-term ratings of the obligor and DTD, over and above the short-term ratings. Combining the results documented above, along with the fact that over 97 per cent of CP issues by volume are given the top rating (A1+), this strongly suggests the need for policymakers to consider a revision of the A1+ category into more granular notches. This will help enhancing the information set of bond markets and enable better pricing of CP issues.

Section II describes the method of construction of the sample and the variables used. Section III presents the results of the empirical analysis. Section IV presents the conclusion and recommendations for policymakers.

II. Sample and Variable Construction

This section outlines the description of the data sources and the screening methodology used to obtain the final sample. In addition, the construction of the main dependent and independent variables is described.

II.1 Data

The initial sample consists of 39,892 commercial paper issues by 555 distinct firms from 2011 to 2018, the data having been obtained from the PRIME database. To obtain accounting and market value information, the Prowess database from the Centre for Monitoring Indian Economy (CMIE) is used.[6] A name matching program in STATA is used to match the firm names from PRIME to the firm names in Prowess. A total of 272 firms are matched using this STATA program, which covers around 75.4 per cent (30,115 observations) of the initial sample.

[6] Although the PRIME database has data from 2003 onwards, a key input for computing the DTD is the amount of short-term debt that the firm has. This data is available from the Prowess database only from 2011 onwards.

Only listed firms are included in the sample because market-capitalization is an important input for the calculation of DTD. This criterion is satisfied for 189 firms. Out of these, 20 firms are dropped because they do not have sufficient trading data for the sample period. Public sector banks and public and state-level undertakings are dropped from the sample, as the spreads of these entities may reflect the effect of implicit guarantees from the Indian government. These screening criteria result in a sample of 13,358 CP issues by 162 distinct issuers.

As a last-level screening, all observations that do not have an A1+ rating are dropped. The rationale is that most issues in the CP market have A1+ rating. As such, studying variation within this sub-category is one of the principal aims of this study. The final screen results in a total of 12,512 issues, which corresponds to 93.66 per cent of observations of the previous sample. These issues correspond to 97.35 per cent of the value of issues. The final sample consists of 152 firms, of which 128 are non-financial and 24 are financial firms, where this categorization is based on PRIME classification. Table 1 presents the results of the data screening process from the initial sample downloaded from the PRIME database to the final sample used in the study.

Table 1: Data Construction

Description	Observations	Firms
Initial Data Sample from PRIME Database 2003-2018	46348	743
Initial Data Sample from PRIME Database 2011-2018	39892	555
Matched from Prowess 2003-18	33654	292
Matched from Prowess 2011-2018	30115	272
Listed Firms matched with distance to default 2011-18	14509	169
Listed firms after dropping State undertakings, PSBs 2011-18	13358	162
Listed firms only A1+ (2011-2018)	12512	152
Non-finance firms	7536	128
Finance firms	5976	24

II.2 Variable construction

The main dependent variable is the spread of the CP yield to maturity over the overnight Mumbai Interbank Offered Rate (MIBOR).[7] All accounting data are taken as of the most recent annual statement from Prowess, where it is assumed that the annual data is released by August 1 of the given year, i.e. three months after the close of the financial year.

For computing DTD, the following variables are required: market capitalization, T-bill rate, short-term debt and long-term debt. Short-term debt is calculated as the sum of short-term borrowings, short-term trade payables and current portion of long-term debt.[8] Total debt is calculated as the sum of short-term debt and half of long-term debt. Data on one year T-bill rate and overnight MIBOR are taken from Bloomberg.

Given the above inputs, DTD is constructed using the methods suggested in Bharath and Shumway (2008). The DTD is computed at the end of the previous month relative to the month of the CP issue to ensure that it does not have any look forward bias. Short-term credit ratings (CP issues) are obtained from the PRIME database. Long-term credit ratings of the CP issuers are obtained from the Prowess database. The long-term ratings used as independent variables are those obtained for term loans, long-term loans, bonds, debentures, and fixed-rate unsecured non-convertible debentures. As multiple long-term ratings may be available for some firms, the most recent long-term rating of the firm prior to the CP issue date is used, as long as the long-term rating date lies within one year prior to the issue date. To the extent that the long-term ratings are not reflective of current information on the credit quality, this should bias against finding any effect of these ratings on the CP spreads.

There are five main credit rating agencies in the data sample—CRISIL, CARE, ICRA, IN-DRA and BRICKWORKS. A standardized measure is created for the credit ratings, by grouping ratings by different agencies into one common rating scale. As all these rating agencies assign almost similar rating categories to long-term debt instruments, this results in a total of four categories of ratings—AAA, AA, A, and BBB. Table 2 provides information on the variables used in the empirical analysis and the source of this data.

[7] The Mumbai Interbank Offered Rate (MIBOR) is calculated everyday by the National Stock Exchange of India (NSEIL) as a weighted average of lending rates of a group of banks, on funds lent to first-class borrowers.

[8] Long-term debt is directly obtained from Prowess under the data item titled 'Long-term borrowings'.

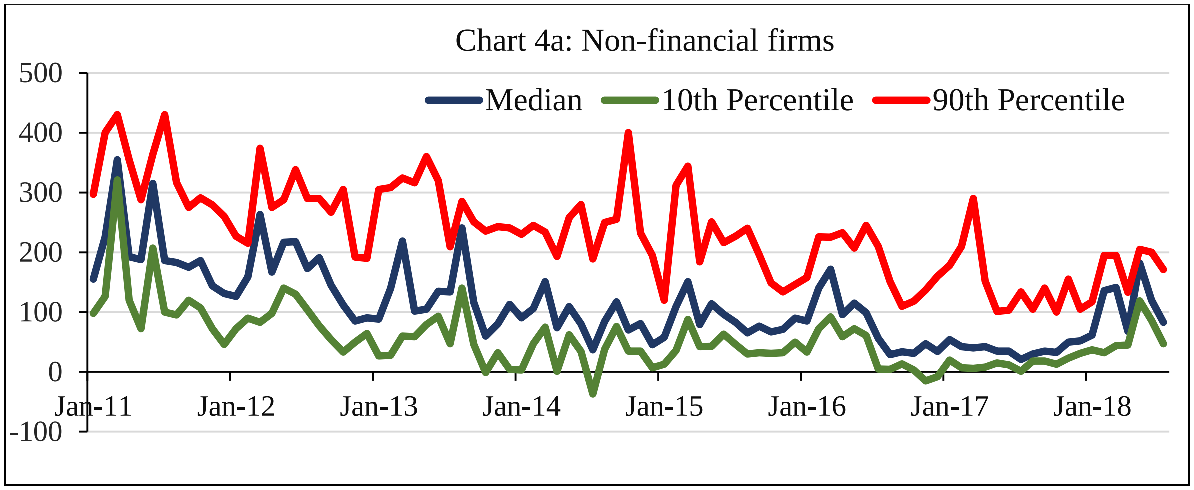
Table 2: Variable Construction

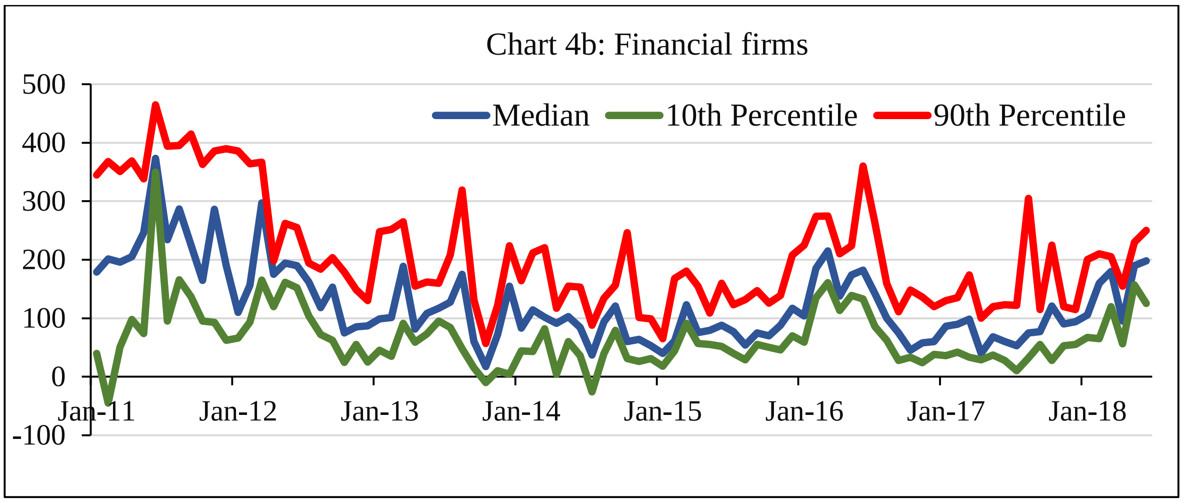
Description	Source
CP Issue Date	PRIME
CP Face Value	PRIME
CP Maturity Date	PRIME
CP Yield	PRIME
Equity	Prowess
Long-term Borrowings	Prowess
Market Capitalization	Prowess
MIBOR	Bloomberg
NIC code	Prowess
Retained profits	Prowess
Sales	Prowess
Short-term Borrowings	Prowess
Spread	Calculated
T-bill Rate	Bloomberg
Total Assets	Prowess

III. Empirical Analysis

III.1 Univariate Results

Charts 4a and 4b present CP spreads over the sample period, starting from January 2011 and ending in July 2018, for non-financial and financial firms, respectively. CP spreads have a large variation within a month for both types of firms. At the monthly level, the average difference between the 10th and the 90th percentiles of spreads is 113 basis points for non-financial firms and 114 basis points for financial firms.





The above suggests a large economically significant variation in credit quality of CP issuers over this time period.[9] Given the above, one natural question to ask is whether these differences in spreads are reflected in the underlying issuer's characteristics. To do this, the sample is divided into two sets based on median spreads for each month: one with observations above the median in a given month and the other with observations below the median in a given month.

Table 3 presents the results of this comparison. These two sets of issuers have different firm-level characteristics. For example, issuers with below median spreads have higher sales turnover (indicating better efficiency of asset use), lower levels of short-term debt and larger firm size. These differences are consistent with the below median firms having lower credit risk, thus resulting in lower spreads of CP issuance.

[9] In other untabulated results, it is found that this is true for the entire period from 2003 for the complete PRIME data without matching to Prowess.

Table 3: Summary Statistics

Variables	Below median	Above median	t-test
Sales over Assets (%)	62.34	40.65	18.18***
Retained Profits over Assets (%)	1.88	1.63	4.77***
Equity over Total Assets (%)	31.88	31.6	0.86
Short-term Borrowings over Assets (%)	16.4	22.27	(23.53)***
Total Assets (INR Cr)	31066	21518	8.01***
Maturity (days)	66.82	99.86	(27.98)***
Issue Size (INR Cr)	109.44	83.52	11.20***

III.2 Multivariate Results

The previous section provided evidence of a large economically significant variation of CP spreads, which can potentially be explained by differences in issuer quality as well as issue characteristics. In this subsection, this variation is examined in a multivariate regression framework, using ordinary least squares (OLS) with fixed effects.

The principal dependent variable (CP Spread) is defined as the difference in the yield to maturity of the CP issue and the overnight MIBOR.[10] The issue size and the log of the maturity of the issue (measured in days) are used to control for issue-level determinants of the spread. For borrower-level controls, the DTD of the borrower, equity ratio and log of total assets are used to control for firm-level determinants of credit risk. In addition, as a key focus of this study is on ratings, the most recent long-term ratings of the borrower are included as dummy variables.

All regressions in the analysis include fixed effects for the day of the issue, as well as the industry of the CP issuer based on the two-digit NIC code of the issuer obtained from Prowess. In addition, to account for possible correlation of error terms, standard errors are clustered at the daily level.

[10] The term spread due to the maturity of the CP issue is explicitly controlled for in the regression as an independent variable.

III.2.1 Baseline Results

Table 4, Panels A and B present the results of the baseline regression. The R^2 of the regressions range from 67 per cent to 69 per cent for non-financial firms, and 77 per cent to 79 per cent for financial firms, suggesting that this simple model captures a large fraction of the variation in CP spreads. Model 1 shows that DTD is a highly significant predictor of spreads for both non-financial as well as financial firms. The log of the face value has a large and negative impact on spreads. This could reflect two factors: (i) economies of scale in issuance costs for larger issues, and (ii) larger issues being undertaken by safer borrowers.[11]

Log of the maturity of the issue is also highly significant, both economically and statistically. In the univariate results, it was observed that issues with above median spreads tend to have longer maturity. The results here are consistent with the previous findings, as maturity has a positive impact on spreads. The key variable of interest, the distance to default or DTD, has a highly significant negative effect on CP spreads providing unambiguous evidence that the CP issue market is fully aware of the different credit quality of different issuances this market.

In Model 2 of Panels A and B, the impact of the overall size of the firm (as measured by the log of the total assets) is examined. In general, one would expect that larger firms should have lower spreads due to lower risk of failure. Surprisingly, for non-financial firms, firm size has a positive correlation with CP spreads, while the reverse is true to financial firms. A potential explanation for these somewhat puzzling results for non-financial firms is that larger borrowers may have a greater leverage or undertake projects with greater risk, which results in greater spread for these issues (Frank and Goyal, 2009). Since the principal interest of this memo is to have a statistical model for predicting spreads, an examination of whether the larger spreads associated with firm size is indeed the result of higher risk for large firms is not undertaken here. Likewise, in Model 3 of Panels A and B, the equity to total assets ratio (where equity includes cumulative retained earnings) has a strong negative effect on spreads for non-financial firms (the anticipated effect) but a strong positive effect on spreads for financial firms. As stated previously, the possibility of endogeneity between the choice of leverage and equity level applies here also.

[11] Given that the principal interest of this memo is in explaining the spread, we do not attempt to distinguish between these two explanations here.

Table 4: Baseline Results

Panel A: Non-finance Firms

	1	**2**	**3**	**4**
Log of Face Value	-14.87***	-15.79***	-12.69***	-15.90***
	(1.24)	(1.48)	(1.27)	(1.47)
Log of Maturity	32.66***	32.08***	32.00***	30.28***
	(2.12)	(2.12)	(2.05)	(2.07)
Distance to Default	-1.736***	-6.704***	-4.254***	-4.715***
	(0.16)	(0.32)	(0.35)	(0.36)
Log of Assets		10.14***		8.587***
		(1.33)		(1.33)
Equity/Total Assets			-126.5***	-114.2***
			(12.15)	(12.02)
Constant	49.20***	-46.61***	98.97***	18.17
	-10.29	-14.41	-11.26	-15.42
No. of Obs.	7306	6924	6924	6924
R squared	0.671	0.684	0.686	0.69

Panel B: Finance Firms

	1	**2**	**3**	**4**
Log of Face Value	-3.501***	-3.072***	-4.229***	-3.945***
	(0.959)	(0.956)	(0.921)	(0.920)
Log of Maturity	18.51***	19.22***	19.06***	19.49***
	(2.773)	(2.839)	(2.684)	(2.749)
Distance to Default	-0.165***	-0.119*	-0.301***	-0.269***
	(0.0589)	(0.0634)	(0.0526)	(0.0560)
Log of Assets		-5.320***		-3.295*
		(1.851)		(1.685)
Equity/Total Assets			101.1***	98.55***
			(10.55)	(10.40)
Constant	58.86***	117.7***	41.68***	78.53***
	(12.00)	(22.74)	(11.81)	(20.32)
No. of Obs.	4610	4610	4610	4610
R squared	0.779	0.781	0.793	0.794

Notes: The dependent variable (CP Spread) is defined as the difference between the yield to maturity of commercial paper and overnight MIBOR. Distance to default (DTD) is constructed using the methods suggested in Bharath and Shumway (2008). All the other independent variables are described in Table 2. Estimation is done using Ordinary Least Squares (OLS). Issue date and industry fixed effects are included in all specifications. Standard errors are clustered at the daily level. ***, **, and * indicate significance at 1, 5, and 10 per cent levels, respectively. Standard errors are shown in parentheses.

III.2.2 Rating effects

In this subsection, the effect of long-term ratings on the spreads is examined. This is done by adding dummy variables for the three main rating categories (AAA, AA, and A) in the regression specifications presented in Table 5.[12] Obligor level controls are not included in this set of regressions, the rationale being that rating agencies should have included all of these variables in the analysis conducted by them to determine the CP ratings.[13]

Long-term ratings have an economically strong impact on credit spreads. For non-financial firms, an issue by a borrower with a long-term rating of AAA has a spread that is 85 basis points higher than an issue by a borrower with a long-term rating of A. The corresponding difference is 42 basis points for financial firms. This effect persists even if one only uses ratings provided by the same rating agency (see Models 2 and 4). In every single model except for one (Model 3, difference in AAA and AA), the difference in spreads across all pairs of rating categories (AAA versus A, AAA versus AA, and AA versus A) is significant, as measured by the F-test for a restricted regression that forces both the dummy variables of these ratings to be equal to each other. This suggests that the differences in rating methodology do not account for differences in the spreads of CP issues.

In Table 6, firm-level controls for credit risk (DTD, issuer total assets and equity ratio) are included as additional controls. These controls do not impact the nature of the aforementioned results. In fact, the magnitude of the effect is similar: 75 basis point difference between AAA and A for non-financial firms (Model 1), and 39 basis points between AAA and A for financial firms (Model 3).

In unreported robustness checks, sub-sample regressions that separate CP issues into three categories are performed: those with a maturity of less than 40 days, those with a maturity from 40 to 100 days, and those with a maturity greater than 100 days.[14] The results are qualitatively and quantitatively similar to those obtained previously. This also holds when the maturity sub-sample analysis is done using ratings provided by the same agency for CP and long-term debt.

[12] As there are very few observations with a long-term rating of BBB, this rating is not included as a control in the analysis. In untabulated results, the effects in Table 5 are robust to inclusion of a fixed effect for BBB rated obligors. However, a dummy variable for BBB obligors itself is insignificant.

[13] In unreported robustness checks, it is found that the addition of borrower-level controls do not impact this result.

[14] Results available from the author on request.

Table 5: Credit Ratings and CP Spreads

	1 Non-finance	2 Non-finance	3 Finance	4 Finance
Log of Face Value	-8.079***	-12.50***	-2.741***	-2.944***
	(1.230)	(1.271)	(0.925)	(0.927)
Log of Maturity	35.43***	34.58***	20.52***	18.98***
	(2.025)	(2.074)	(2.720)	(2.768)
AAA Rating	-23.83***		-37.24***	
	(4.581)		(9.001)	
AA Rating	-7.829***		-33.19***	
	(2.766)		(8.428)	
A Rating	61.32***		4.889	
	(4.171)		(9.765)	
Same Rating Agency, AAA Rating		-42.83***		-27.45***
		(4.972)		(4.500)
Same Rating Agency, AA Rating		-28.47***		-7.353***
		(2.665)		(2.173)
Same Rating Agency, A Rating		19.01***		18.63***
		(4.125)		(4.108)
Constant	-2.880	38.90***	73.92***	56.52***
	(10.06)	(10.06)	(14.70)	(12.09)
No. of Obs.	7306	7306	4610	4610
R squared	0.71	0.68	0.79	0.78
P-value AAA=AA	0.00	0.00	0.14	0.00
P-value AA=A	0.00	0.00	0.00	0.00
P-value AAA=A	0.00	0.00	0.00	0.00

Notes: The dependent variable (CP Spread) is defined as the difference between the yield to maturity of commercial paper and overnight MIBOR. Distance to default (DTD) is constructed using the methods suggested in Bharath and Shumway (2008). All other variables are described in Table 2. Estimation is done using Ordinary Least Squares (OLS). The p-value denotes the significance of the F-test of the restricted regressions. Deal date and industry fixed effects are included in all specifications. Standard errors are clustered at the daily level. ***, **, and * indicate significance at 1, 5, and 10 per cent levels, respectively. Standard errors are shown in parentheses.

Table 6: Credit Ratings and Spreads: Additional Controls

	1 **Non-finance**	**2** **Non-finance**	**3** **Finance**	**4** **Finance**
Log of Face Value	-12.01***	-14.60***	-3.552***	-3.496***
	(1.371)	(1.438)	(0.910)	(0.899)
Log of Maturity	32.08***	31.12***	20.38***	19.73***
	(2.007)	(2.056)	(2.720)	(2.755)
Distance to Default	-3.257***	-4.156***	-0.173***	-0.199***
	(0.360)	(0.346)	(0.0571)	(0.0560)
Equity/Total Assets	-88.97***	-110.5***	89.02***	90.28***
	(11.25)	(11.79)	(9.523)	(10.29)
Log of Assets	13.35***	10.93***	0.348	-2.999*
	(1.419)	(1.349)	(1.781)	(1.755)
AAA Rating	-30.91***		-18.34*	
	(5.188)		(9.609)	
AA Rating	-17.62***		-13.83	
	(2.922)		(8.524)	
A Rating	44.10***		21.07**	
	(4.273)		(9.505)	
Same Rating Agency, AAA Rating		-32.21***		-14.41***
		(5.206)		(5.176)
Same Rating Agency, AA Rating		-26.65***		-3.239
		(2.570)		(2.197)
Same Rating Agency, A Rating		16.22***		17.14***
		(3.885)		(4.067)
Constant	-68.81***	-5.967	40.77*	74.24***
	(17.27)	(15.65)	(21.02)	(21.36)
No. of Obs.	6924	6924	4610	4610
R squared	0.72	0.71	0.80	0.80
P-value AAA=AA	0.00	0.26	0.13	0.03
P-value AA=A	0.00	0.00	0.00	0.00
P-value AAA=A	0.00	0.00	0.00	0.00

Notes: The dependent variable (CP Spread) is defined as the difference between the yield to maturity of commercial paper and overnight MIBOR. Distance to default (DTD) is constructed using the methods suggested in Bharath and Shumway (2008). All other variables are described in Table 2. Estimation is done using Ordinary Least Squares (OLS). The p-value denotes the significance of the F-test of the restricted regressions. Deal date and industry fixed effects are included in all specifications. Standard errors are clustered at the daily level. ***, **, and * indicate significance at 1, 5, and 10 per cent levels, respectively. Standard errors are shown in parentheses.

IV. Conclusion

This study investigates the efficiency of the commercial paper (CP) market in India using spreads of CP issues. Market-implied probability of default (which is measured using the Merton's distance to default) as well as accounting variables have a consistent and significant effect on CP spreads. In addition, several issue and issuer characteristics have a strong impact on spreads. The above suggests that buyers in the CP market are fully aware of and price credit risk appropriately.

The most important result from a policy standpoint is that there is a strong impact of long-term ratings on the spreads of CP issues within a set of issuers with an identical CP rating. In particular, there is a 40 to 80 basis points difference in the spread of an issuer with a long term rating of AAA versus an issuer with a long term rating of A. This effect persists even if the same rating agency rated the CP issue and also provided the long-term rating. This suggests that rating agencies may consider a finer rating category for CP issues, e.g. using more granular notches within a rating category, to provide a greater degree of information to market participants in the bond market. Given that rating agencies have well established methods to compute long-term ratings, implementing the above suggestions may not be difficult.

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