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Market Implied Ratings and Financing Constraints: Evidence from US Firms

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Abstract: Financing constraints have been found to play an important role in several aspects of firm behavior, but no attention has been given to their effects on credit ratings. In this paper we analyze a unique and comprehensive data set for US firms rated by Fitch over the period 2001–07. We employ Fitch's market implied ratings derived from bond and equity prices. The analysis finds evidence that financial variables are more important in predicting credit ratings for firms likely to face financing constraints. We conclude that the financing constraint is an important dimension in the market implied ratings process. Our findings are of relevance to managers, investors and rating agencies seeking to understand the mechanism through which financing constraints affect credit ratings.

Keywords: financing constraints, credit ratings, ordered probit

1. INTRODUCTION

Numerous empirical studies have attempted to understand how capital market imperfections affect firm behavior. Since the seminal contribution of Fazzari et al. (1988) (FHP hereafter), who provided evidence that financial constraints matter for corporate investment, several studies have highlighted the importance of financing constraints in firms' real decisions such as fixed investment, inventory investment, employment and R&D activities (see Hubbard, 1998 for a survey). A significant challenge to FHP's (1988) results came by Kaplan and Zingales (1997), who concluded that higher sensitivities of investment to cash flow cannot be interpreted as evidence that firms are more financially constrained.[1] An attempt to reconciliate the seemingly contradictory findings in Fazzari et al. (1988) and Kaplan and Zingales (1997) was

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1 Other authors use savings —cash flow models as an alternative way of testing for the existence of financing constraints (see for instance D'Espallier et al., 2008).

made by Guariglia (2008), who showed that these results are probably due to the different partitioning criteria used in each study.[2]

Beyond the influences of financial constraints on firms' behavior, there is a growing set of studies on the determinants of credit ratings. This literature considers the importance of financial and business risks in predicting credit ratings (see Pogue and Soldofski, 1969; Pinches and Mingo, 1973; Kaplan and Urwitz, 1979; and Kao and Wu, 1990) as well as the behavior of ratings over time –i.e., the consideration of increased volatility in corporate creditworthiness during the mid-1980s and early 1990s and the accompanied downward momentum (see Blume et al., 1998; Amato and Furfine, 2004; and Pagratis and Stringa, 2009). What is less researched, however, is the role of financial constraints in firms' credit ratings.

The present paper seeks to fill this gap by bridging the literatures on financing constraints and credit ratings. More specifically, the purpose of this paper is to provide, for the first time, a systematic empirical analysis of the impact of financing constraints on market implied ratings by exploring whether financial information is weighted differently for financially constrained versus unconstrained firms. In doing so, we aim to understand whether the financing constraint is an important dimension in the rating process. Our motivation for exploring the role of financing constraints in credit ratings stems from the fact that ratings changes (especially downgrades) can have a disproportionate impact on an issuer's cost and availability of capital, the price of bonds, and, occasionally, equity. These effects will be stronger for financially constrained firms, for whom access to external finance may be difficult or prohibitively expensive. Such evidence is important for understanding the mechanism through which financing constraints affect credit ratings and can be used to better inform ratings agencies and investors, especially in the current economic climate.

The value added of the present paper is twofold. First, we determine whether the agencies' approach to rating assignment systematically accounts for the firm-specific risks associated with the firm's balance sheet information. While there is an established literature on firms' real activities and financing constraints, we examine for the first time whether ratings allow for firm-level heterogeneity. Thus we contribute to the credit ratings literature by investigating whether the financing constraint is an important dimension in the market implied ratings process, since this characteristic dramatically alters perceptions of creditworthiness, access to credit and defaults.

The second main contribution is that we make use of a novel credit risk measure, namely the market implied ratings, determined from credit default swaps (CDS) and equity market data. This is important if we consider that the accuracy and the timing of credit ratings have been heavily criticized, especially during turbulent economic times. Therefore, market-based credit risk measures were introduced in response to these concerns. Moody's (2007) argue that CDS provide more accurate signals of credit risk compared to corporate bonds, while Fitch (2007) note that CDS have the advantage of being pure, light and liquid. Therefore, CDS can be used as bond substitutes.[3] In our study, we move this literature forward by considering the determinants of market implied ratings and their response to financing constraints.

2 In addition, Guariglia and Mateut (2006) use the idea of trade credit as a new explanation for why some financially constrained firms may exhibit low investment–cash flow sensitivities suggesting that these firms make a heavy use of trade credit, offsetting therefore their liquidity constraints.

3 The growth of the CDS market has been spectacular and it now covers over half of the credit derivatives market (see Castellano and Giacometti, 2012).

The paper is organized as follows. In section 2 we summarize the rating process in credit ratings agencies. We present the data used in our empirical analysis in section 3, and we discuss our econometric modeling strategy in section 4. In section 5 we report the model predictions. In section 6 we check the robustness of our findings, and we provide concluding comments in section 7.

2. CORPORATE FINANCE AND RATING METHODOLOGY

Ratings provided by credit risk agencies are an assessment of the issuer's ability to service debt in a timely manner and are intended to be comparable across industry groups and countries. The ratings assigned from these agencies are expressed in letter form, ranging from AAA (Aaa for Moody's), the highest, to C, the lowest. The division of the rating scale into these buckets is intended to divide a continuum of risk into discrete risk classes based on an assessment of the capacity of the debt issuer to meet its ongoing financial obligations. The highest rating, AAA, indicates an extremely strong capacity to pay interest and repay the principal debt, while the lowest rating, C, indicates a serious vulnerability to default on payment. Debt rated from AAA to BBB is considered 'investment' grade, while debt rated at BB and below is considered "speculative" grade. Three rating agencies, Moody's, Standard and Poor's and Fitch, have a long history and dominate the US credit rating industry. The first two agencies have a policy of rating all taxable corporate bonds publicly issued in the US, while Fitch rate issuers on request. The bond ratings provided by these agencies are generally comparable and the rating scales are found to be uniform.[4]

The large number of rating downgrades during the US corporate credit meltdown in 2001–02 and the recent global financial crisis have focused attention on the rating agencies and the process through which they assign ratings to firms and their financial instruments. More specifically, one of the main concerns has been the fact that ratings are slow to adjust to changes in risk and therefore can be "sticky" (Kou and Varotto, 2008). In response to these concerns, market-based credit risk measures were introduced to provide accurate estimates over short time horizons, such as 1 year. One such measure is the market implied ratings which have become increasingly popular in the industry because they are intended to capture the market risk.[5] Market implied ratings, also known as "point in time" ratings, are determined from CDS and equity market data that change as prices move and fully reflect cyclical and other influences on a firm's likelihood of default. These ratings rely on proprietary and data-intensive rating models that incorporate market information into a model-based credit assessment.

The literature on market implied ratings has focused on the comparison between long-term agency ratings and market implied ratings. Breger et al. (2003) classify bonds using bond spreads and note a significant improvement in the forecasting ability of the models. Hence they conclude that implied ratings are a "simple, intuitive, and attractive tool". Rösch (2005) compares long-term ratings with point in time (or implied) ratings and considers the differences in methodology to be fundamental. He concludes that point in time ratings produce more precise default probability forecasts

4 Cantor et al. (2007) compare the ratings of Moody's, Standard and Poor's and Fitch and conclude that "when all ratings from all sectors are combined, on average, current ratings assigned for jointly-rated instruments differ by less than one notch".

5 Moody's and Fitch made these ratings available to the public in 2003.

compared to long-term ratings. Kou and Varotto (2008) use evidence on convergence of implied ratings from bond spreads and conventional issuer default measures, finding that spread-implied ratings have predictive power up to 6 months ahead for Moody's and Standard and Poor's long-term ratings. More recently, Castellano and Giacometti (2012) examine whether changes of market implied ratings lead or lag the effective agency ratings changes, paying special attention to the most recent financial crisis.[6]

Fitch has recently developed two methodologies for deriving market implied ratings. The equity implied ratings model (EQIR) processes the firm's credit condition given its current equity price and available financial condition. It then calculates and converts these into equity implied ratings (see Liu et al., 2007). The equity implied ratings are based on the Merton (1974) option pricing formula. The equity price of a firm is treated as a call option on the assets of the firm and from this the rating agency can derive expected default frequencies. These measures are compared to actual default frequencies to create an equity implied credit rating on the same scale as conventional issuer default ratings. Three factors are used to determine Fitch's expected default frequencies. These are: i) financial ratios, ii) market performance, and iii) market risk.[7] On the other hand, the CDS implied ratings model (CDSIR) is estimated to provide the collective marketplace view of firms' credit condition based on its current CDS pricing, financial information, region and industry (see Fitch, 2007). The price of a CDS contract as the cost of protection against default is similarly related to the expected default frequency (see Hull et al., 2004).[8] The upshot is that while EQIR refers to the equity market and the CDSIR refers to the CDS market, both market implied methodologies were developed in order to capture volatile market changes.

3. DATA

(i) Data Sources

We use Fitch's database as our source for data on market implied ratings. This database provides information on the Equity and CDS implied rating assigned to each issuer as well as the date that the rating became available. Thus we can record the continuous rating history for each firm. Both Equity and CDS implied ratings cover the period 2001 to 2007 for all traded non-financial firms in the US. In keeping with the normal practice in the literature, we categorize our firms into rating categories without consideration of notches (i.e., − or −). Amato and Furfine (2004) emphasize that this categorization considers large cumulative changes of ratings rather than small movements notch by notch, and avoids the generation of rating categories with very

6 Similar tests have been carried out by the ratings agencies themselves, confirming that market implied ratings models are more effective, compared to alternative models, at predicting ratings changes (see Fitch, 2007; and Moody's, 2007).

7 Fitch uses a set of ratios that cover different measurement categories such as activity, coverage, leverage, liquidity and profitability. With respect to market performance, Fitch relies on the volatility of the firm, while market risk is commonly tested using macro-economic market variables.

8 Batta (2011) finds that both leverage and earnings are important determinants of CDS pricing. For a theoretical exposition on the pricing of credit risk of secured debt and financial leasing see Realdon (2006).

few observations. We consider seven rating categories, ranging from AAA to CCC, which are assigned numerical values, starting with 1 to AAA, 2 to AA, . . . , 7 to CCC.

Firm-level accounting data are taken from Datastream. We use data for five industries: manufacturing, utilities, mining, services and financial services. This classification corresponds to the sectoral breakdown of the entire US economy using the Datastream level 3 sector indices, constructed according to the 1999 FTSE reclassification. Following selection criteria commonly used in the literature, we exclude companies that do not have complete records on our explanatory variables and firm-years with negative sales and assets. To control for the potential influence of outliers, we exclude observations in the 0.5% upper and lower tails of the distribution of the regression variables.

Our combined sample contains data for 273 firms yielding a total number of 1,543 annual observations for Equity implied ratings and 1,603 annual observations for CDS implied ratings. The panel has an unbalanced structure with the number of observations on each firm varying between two and seven. Our sample presents two characteristics that make it especially appealing for our analysis. First, it includes both investment grade and high yield bonds. This contrasts with previous studies, which mainly restricted their attention to investment grade bonds, neglecting the effects of speculative grade bonds. Inclusion of the two categories is particularly beneficial since firms with high yield bond issues are more likely to be characterized by adverse financial attributes and weak balance sheets, hence, these firms are more likely to be financially constrained. Second, the distribution of agency (long-term) ratings in CDS data is very similar to the distribution of agency ratings in the general bond population (see Fitch, 2007). Thus both the CDSIR and the EQIR databases can provide a representative base for conducting our empirical analysis.

(ii) Sample Separation Criteria

A large literature has considered the impact of financial constraints on investment in fixed capital, inventory investment, employment and R&D activities (see Hubbard, 1998 for a survey). In many cases the response of firms to indicators of creditworthiness is found to be dependent on whether firms are likely to be "financially constrained" or "financially unconstrained". However, the results can be influenced by the categorization process used to determine whether firms are financially "constrained" or "unconstrained" (see, e.g., Fazzari et al., 1988, 2000; and Kaplan and Zingales, 1997, 2000).[9] The scholarly literature has not settled on a universally accepted strategy to identify financially "constrained" and "unconstrained" firms empirically, but the classification scheme can be critically important for the conclusions of these studies. Therefore, in this paper we employ the dividend payout ratio as our main measure of financing constraint, but we check the robustness of our findings using two additional measures: i) firms' size, and ii) the degree of bank dependency.

The dividend payout ratio, as measured by the ratio of total dividends to income, has been used by a number of studies (see, for example, Fazzari et al., 1988, 2000; and Angelopoulou and Gibson, 2009) because it is argued that firms will refrain from distributing earnings if they expect to rely on these for real investment, and they will

9 For a discussion of financial constraints see the recent literature on firms' real decisions (Carpenter and Guariglia, 2008; D'Espallier et al., 2008; Spaliara, 2009; Dang, 2011; and Mizen and Tsoukas, 2012b).

do so if they are financially constrained. We partition our firms according to whether they are more or less likely to face financing constraints using the 25% cut-off point. Specifically, we create a dummy variable *CONS*, which is equal to one if the firm's dividend payout ratio is in the bottom 25th percentile of the distribution of dividends of all the firms in that particular industry and year, and zero otherwise.[10] Finally, we allow firms to transit between firm classes.

(iii) Measures of Risks

Market implied ratings models typically incorporate financial statement information and market information (see Fitch, 2007; and Liu et al., 2007). The former can be operationalized with a group of financial indicators which are intended to capture the firm's balance sheet healthiness. The latter refers to firm risk/performance and market volatility. In our empirical model we follow both the ratings agencies' practice and the recent literature in measuring these risks using a number of explanatory variables. In order to select the best possible model, we consider the improvement of the Likelihood Ratio (LR) test and the achievement of the best in- and out-of-sample predictive performance.[11]

To begin with the financial information, we rely on five indicators of balance sheet healthiness: i) leverage, ii) coverage, iii) liquidity, iv) cash flow, and v) profitability. We also include the firm's size to capture business risk (see Amato and Furfine, 2004). Leverage (*LEV*) defined as total debt over total assets indicates the overall indebtness of the firm. Higher leverage implies a weaker balance sheet and we expect this measure to have an adverse effect on implied ratings. The coverage ratio (*COV*) is measured as earnings before interest and taxes over interest payments. It is a measure of creditworthiness since it indicates the ability of the firm to service its existing debt. We expect that a higher coverage ratio gives a positive signal of a healthy balance sheet and thus should improve a firm's implied rating. Liquidity (*LIQUID*) indicates the cash from operations relative to liabilities, and would improve the credit rating. Cash flow (*CF*) is a measure of the resources the firm is able to generate from its operations relative to its total assets.[12] Greater cash flow would also improve the credit rating if it were to increase. Profitability (*PROF*) is defined as earnings before interest and taxes over total assets. Higher profitability would improve the credit rating. Finally, the log of real total assets (*SIZE*) indicates the size of the firm and would expect larger firms to attract better ratings, all else equal.

Market performance is a dimension which can be captured by the asset value and volatility of a firm (Liu et al., 2007). To measure firm risk/performance we use the firm's volatility in sales. As an alternative measure of firm risk we have considered the CDS spreads which capture the CDS market risk. These results are reported in the robustness section. Firm volatility affects its borrowing capacity and thus impacts on the firm's ability to refinance its debt. This will ultimately be reflected in the firm's

10 In section 6 we employ the 50th percentile and we find that our results are robust to alternative cut-off points.

11 The LR test compares the log likelihoods of two competing models and tests whether this difference is statistically significant. The predictive performance of the models is based on the *SC* and *CP* scores, which are discussed in section 4.

12 We have opted for the operating cash flow rather than the sum of net income plus depreciation due to missing observations in the latter variable.

Table 1

Equity Implied Ratings Per Year

	AAA	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*Observations*
2001	0	8	46	79	63	20	0	216
2002	1	8	57	95	49	8	0	218
2003	3	19	100	70	26	4	0	222
2004	0	5	69	85	53	11	0	223
2005	0	7	69	78	51	17	0	222
2006	1	10	84	71	46	16	0	228
2007	0	9	63	69	49	23	1	214
Observations	5	66	488	547	337	99	1	1,543

Notes:
The table presents the distribution of firms' equity market implied ratings by year based on a panel of firms from 2001 through 2007.

Table 2

CDS Implied Ratings Per Year

	AAA	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*Observations*
2001	6	2	46	79	63	20	0	216
2002	1	8	57	95	49	8	0	218
2003	7	38	36	64	39	15	4	203
2004	5	30	48	68	54	22	7	234
2005	8	18	49	70	55	32	6	238
2006	5	22	53	69	56	31	12	248
2007	12	33	33	65	44	40	19	246
Observations	44	151	322	510	360	168	48	1,603

Notes:
The table presents the distribution of firms' CDS implied ratings by year based on a panel of firms from 2001 through 2007.

implied rating. Thus, we should expect to find that more volatile firms attract worse implied ratings. Following Comin and Mulani (2005) and Garcia-Vega et al. (2012) we define firm volatility as the standard deviation of the firm's real sales growth, measured over a rolling window of 3 years. Specifically, $Volatility_{it} = [\frac{1}{3}\sum_{\tau=-3}^{0}(sales_{i(t+\tau)-\mu_{it}})^2]^{\frac{1}{2}}$ where i denotes firms and t time, $sales$ stands for the growth in real sales of firm i at time t, and μ_{it} its average sales growth which is measured over the 3 years preceding and including year t.[13]

(iv) Descriptive Statistics

Table 1 reports the distribution of firms' equity implied ratings by year, while Table 2 provides the same information on firms' CDS implied ratings. We can observe that the number of observations is evenly spread over time and that our sample is mainly dominated by observations with A and BBB implied ratings.

13 Due to the construction of the volatility measure, all the regressions are based on the period 2003-07. The results were robust to calculating volatility over the 5 years preceding and including year *t*. However, this leads to the loss of a considerable number of observations. The results are not reported, but are available upon request.

Table 3
Summary Statistics for Firm-Specific Variables used in the Empirical Models

	All firms (1)	*CONS = 1* (2)	*CONS = 0* (3)	*Diff.* (4)
EQIR	3.80	4.66	3.72	0.00
	(0.97)	(0.88)	(0.94)	
CDSIR	3.90	5.20	3.77	0.00
	(1.39)	(1.16)	(1.34)	
LEVER	30.43	39.05	29.57	0.00
	(17.05)	(24.09)	(15.95)	
COV	5.95	3.89	6.15	0.00
	(4.32)	(3.46)	(4.34)	
LIQ	13.01	12.21	13.09	0.58
	(15.64)	(15.69)	(15.14)	
CF	10.51	6.80	10.88	0.00
	(5.35)	(5.18)	(5.63)	
PROF	10.00	5.97	10.40	0.00
	(5.90)	(6.61)	(5.67)	
SIZE	9.36	9.17	9.38	0.03
	(0.98)	(0.79)	(0.99)	
VOL	0.11	0.12	0.11	0.45
	(0.12)	(0.10)	(0.12)	
Observations	1,121	101	1,020	

Notes:
The table presents sample means. Standard deviations are reported in parentheses. The *p*-value of a test of the equality of means is reported. *CONS* is a dummy variable which takes the value one if the firm's dividend payout ratio is below the bottom 25th percentile of the distribution of the dividend payout ratio of all the firms in that particular industry and year, and zero otherwise. *EQIR* is the equity implied rating. *CDSIR* is the CDS implied rating. *LEVER* is measured as the firm's total debt to assets ratio. *COV* is measured as earnings before interest and taxes over interest payments. *LIQ* is defined as the ratio of cash from operations relative to total liabilities. *CF* is given by the ratio of cash from operations to total assets. *PROF* is defined as earnings before interest and taxes over total assets. *SIZE* is defined as the log of real assets. *VOL* is the firm's volatility in sales calculated as shown in section 3(iii). Variables are measured in thousands of US dollars.

Summary statistics for the firm-specific variables used in our empirical analysis are provided in Table 3.[14] In column (1) we present figures for the whole sample, while columns (2) and (3) refer to firm-years, which are respectively financially constrained and unconstrained based on the dividend payout criterion. A final column reports the *p*-value of a test for whether there is a significant difference between values for constrained and unconstrained firms. We observe that firms which are categorized as constrained have worse market implied ratings (recall that a lower number indicates a higher rating category i.e., 1 = AAA, 2 = AA etc). In addition, financially constrained firms display higher levels of leverage, lower levels of interest coverage, liquidity, cash flow and profitability. Therefore, consistent with the financing constraint literature we find that financially constrained firms are in bad financial shape compared to unconstrained firms. In addition, constrained firms are smaller and more volatile compared to their unconstrained counterparts. These differences between sub-samples are statistically significant in all cases with the exception of liquidity and volatility. To sum up, we show that market implied

14 These statistics are calculated based on the number of observations used in the regressions.

ratings and financial health are inversely related and that there are significant differences between financially constrained and unconstrained firms. The latter statistic illustrates the relevance of firm-level heterogeneity to the understanding of the firm's ratings.

4. EMPIRICAL IMPLEMENTATION

Credit ratings can be viewed as resulting from a continuous, unobserved creditworthiness index. Each rating corresponds to a specific range of the creditworthiness index, with higher ratings corresponding to higher creditworthiness values. Therefore, credit ratings are discrete-valued indicators and have an ordinal ranking. Typically, credit ratings are modeled through an ordered probit methodology (see, for example, Adams et al., 2003; Alfonso et al., 2007; Amato and Furfine, 2004; Blume et al., 1998, and Pagratis and Stringa, 2009).

(i) Baseline Specification

The model description follows Maddala (1983). We define the categorical variable $y = 1, 2, \dots, 7$ according to the actual market implied rating assigned to each firm. Without loss of generality we record AAA as 1, AA as 2 … CCC as 7. This ordinal response can be modeled through a standard ordered probit model of the following type:

$$y_{it}^{*} = X_{it-1}\beta_1 + Z_{it}\beta_2 + \epsilon_{it}, \tag{1}$$

where $i = 1, \dots, N$ refers to firms and $t = 1, \dots, T$ refers to time periods. Vector X considers five dimensions of financial health, namely leverage, coverage, liquidity, cash flow and profitability. All financial variables are lagged one period to mitigate potential endogeneity concerns. Vector Z includes our control variables which are all chosen in view of other work on credit ratings and what is available in the data. Specifically, we include the firm's size and volatility in sales. The model also includes time and industry dummies to control respectively for macro-economic effects and for the unique influence of factors affecting specific industrial groups. ϵ_{it} is the disturbance term which is assumed to be normally distributed with zero mean and unit variance.

In our data y_{it}^{*} is not observed. Thus what is observed are the market implied ratings assigned to firms, which can take seven values. The relationship between the observed variable y_{it} and the latent variable y_{it}^{*} is assumed to be given by:

$$\begin{aligned}
y_{it} &= AAA \quad \text{if} \quad y_{it}^{*} \le \gamma_1 \\
y_{it} &= AA \quad \text{if} \quad \gamma_1 \le y_{it}^{*} < \gamma_2 \\
&\dots \\
y_{it} &= CCC \quad \text{if} \quad \gamma_7 \le y_{it}.
\end{aligned}$$

Thus the probability of y^*_{it} being in a particular rating category can be estimated as:

$$Pr(y_{it} = 1) = Pr(y^*_{it} < \gamma_1) = Pr(X_{it-1}\beta_1 + Z_{it}\beta_2 + \epsilon_{it} < \gamma_1)$$
$$Pr(y_{it} = 2) = Pr(\gamma_1 \leq y^*_{it} < \gamma_2) = Pr(\gamma_1 \leq X_{it-1}\beta_1 + Z_{it}\beta_2 + \epsilon_{it} < \gamma_2)$$
$$\ldots$$
$$Pr(y_{it} = 7) = Pr(y^*_{it} < \gamma_7) = Pr(X_{it-1}\beta_1 + Z_{it}\beta_2 + \epsilon_{it} < \gamma_7).$$

The latent variable y^*_{it} can then be estimated through standard maximum likelihood. The sign of the regression parameters β can be interpreted as determining whether or not the latent variable y^*_{it} increases with the regressor.

(ii) Constrained/Unconstrained Firms

Following earlier empirical studies (see Angelopoulou and Gibson, 2009; Guariglia, 2008; and Guariglia, 1999) we interact the financial constraint dummy vector, $CONS$, with our measures of balance sheet healthiness to determine whether the rating probability assigned by the ordered probit model varies with this categorization. In addition, we allow the financial constraint dummy to influence credit ratings directly:

$$y^*_{it} = X_{it-1}\beta_1 CONS_{it} + X_{it-1}\beta_2(1 - CONS_{it}) + CONS_{it}\beta_3 + Z_{it}\beta_4 + \epsilon_{it}. \quad (2)$$

Here the dummy vector $CONS$ is interacted with the vector of firm-specific financial variables (X) in our specification. It will be apparent from these models whether financial information is weighted differently for financially constrained versus unconstrained firms by the significance of the coefficients on the interacted term. Significant differences between the interacted coefficients would indicate that the financing constraint is an important dimension in the market implied ratings process. Moreover, financial constraints are allowed to influence the probability of being assigned a rating directly, judged from the sign and significance of the coefficient β_3.

(iii) Predictive Ability

We evaluate the proportion of correct predictions from each empirical model to directly assess the predictive ability of ratings. In doing so, we rely on two measures of predictive ability, the *SC* and *CP* scores based on the proportions of correct predictions versus actual outturns.

The proportion of correct predictions denoted as *SC* is the sum of all diagonal terms divided by the total number of observations: that is $SC = \frac{1}{T}\sum_{t=1}^{T} 1(\hat{q}_t = q_t)$ where $\hat{q}_t$ refers to the predicted rating and q_t is the actual outcome. This measure is a simple summary of predictive ability, but it is possible that this measure is greatly affected when there is a dominant outcome in the data.[15] The measure *SC* cannot distinguish

15 If for example 70% of issuers are rated AA, then a prediction of AA for all firms will appear to predict correctly in 70% of cases. This is an illusion since the model does not use the explanatory variables to make

between seemingly successful predictability of a "stopped clock" and true predictability. A second measure based on a technique proposed by Merton (1981) and used in Henriksson and Merton (1981), Pesaran and Timmermann (1994), Chevapatrakul et al. (2008) and Mizen and Tsoukas (2012a) can modify the *SC* measure in order to get a better indicator of the predictive ability. Let CP_j be the proportion of the correct predictions made by $\hat{q}_t$ when the true state is given by $q_t = j$. From the definition of conditional probability, *CP* is computed as $CP_j = \frac{\frac{1}{T}\sum_{t=1}^{T} 1(\hat{q}_t=j)(q_t=j)}{\frac{1}{T}\sum_{t=1}^{T} 1(q_t=j)}$ and the Merton's correct measure denoted *CP* is given by $CP = \frac{1}{J-1}[\sum_{j=0}^{J-1} CP_j - 1]$ where J is the number of categories, and $-\frac{1}{J-1} \leq CP \leq 1$. In the contingency table *CP* is the unweighted average of CP_j's minus one (to correct for the stopped clock phenomenon). The CP_j's are calculated as the proportion of correct predictions divided by the total of each row. This modifies the measure of predictive ability to discount the influence of the dominant outcome. A high *CP* score indicates that the predictor is accurate for all rating categories.

5. RESULTS

(i) Baseline Model

We begin our enquiry with a basic model of market implied ratings determination as shown in equation (1). In column (1) of Table 4 we present the results for the EQIR, while those for the CDSIR are shown in column (2). Taking the financial variables we observe that leverage (*LEV*) has a positive coefficient and is highly significant. This result implies that firms with high levels of debt, which is typically interpreted as a sign of poor balance sheet position, are likely to attract lower credit ratings. In addition, the coverage ratio (*COV*), the liquidity (*LIQ*), the cash flow (*CF*) and the profitability (*PROF*) have negative coefficients showing that creditworthy firms and those with higher cash flows liquidity and profitability levels have a higher probability to obtaining a better rating.[16] These results are consistent with in-house research by rating agencies and existing evidence in suggesting that better financial ratios increase the probability of being assigned a better rating (Blume et al., 1998; Adams et al., 2003; Amato and Furfine, 2004; Alfonso et al., 2007; and Pagratis and Stringa, 2009).

Moving to firm volatility (*VOL*), we observe positive and significant coefficients in both models. Thus, more volatile firms, which are riskier and face a higher chance of failure, are more likely to get a worse rating. We also find that the size of the firm (*SIZE*) attracts negative and significant coefficients. We conclude that larger firms are more likely to attract improved ratings. This result confirms the information asymmetry problem that small firms are likely to face, and is consistent with research that suggests that high costs of external finance are related to asymmetric information (see Carpenter et al., 1994; and Calomiris and Hubbard, 1995).

Judging from the signs of the estimated coefficients, in both the EQIR and the CDSIR models, we find that an increase in interest coverage, liquidity, cash flow, profitability and size reduce the probability of being assigned a worse rating

different predictions of the probability of rating assignment, but makes only one prediction for all issuers irrespective of the information on business and financial risks.

16 The only exceptions are the liquidity and cash flow variables for the CDS implied ratings, which enter with the expected negative sign, but they are not statistically significant.

Table 4
Baseline Models

	EQIR (1)	*CDSIR* (2)
LEV	0.043***	0.030***
	(11.27)	(10.53)
COV	0.020	-0.054***
	(1.28)	(-3.67)
LIQ	−0.027***	−0.002
	(−6.07)	(−0.76)
CF	−0.048***	−0.016
	(−3.37)	(−1.40)
PROF	−0.105***	−0.079***
	(−7.87)	(−6.53)
SIZE	−1.085***	−0.605***
	(−17.00)	(−14.64)
VOL	1.418***	0.618**
	(3.33)	(2.06)
Observations	1,124	1,121
$Pseudo - R^2$	0.48	0.29
Marginal effects when rating = A		
LEV	−0.96	−0.71
COV	−0.006	1.28
LIQ	0.88	0.005
CF	2.10	0.38
PROF	3.40	1.89
SIZE	35.23	14.53
VOL	−46.03	−14.84

Notes:
The table presents ordered probit estimation results. The left-hand side variable is the market implied rating of a firm. In the analysis AAA ratings are assigned a "1", AA a "2", and so on until CCC ratings, which are assigned a "7". Time and industry dummies were included in all specifications. All financial variables are lagged one time period. Robust z-statistics are reported in the parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Also see notes to Table 3.

(i.e., categories 4, 5, 6 and 7) and increase the probability of being assigned an improved rating (i.e., categories 1, 2 and 3). On the other hand, in both models, a higher value of leverage and firm volatility reduces the probability of being assigned a 1, 2 or 3 rating and increases the probability of a 4, 5, 6 or 7 rating. However, in order to interpret the estimated coefficients of the ordered probit models we need to examine their corresponding marginal effects (Greene, 2008). We calculated the marginal effects as the percentage change in the probability of being in a particular rating category due to a 1% increase in each of the explanatory variables. We report marginal effects at the bottom of Table 4. In the interest of saving space we concentrate on rating A, which is one of the most populated rating categories in our sample.[17] In terms of economic significance, let us take the examples of leverage and cash flow for both EQIR and CDSIR models. A 1% increase in leverage would

17 As noted above, the interpretation of marginal effects is dependent on our choice of the rating category. For instance, the negative sign on the marginal effect for leverage remains unchanged when we consider the improved ratings (i.e., categories 1, 2 and 3), while becomes positive when we consider the remaining rating categories (i.e., categories 4, 5, 6 and 7).

reduce the probability of a given rating to be ranked A (category 3) by 0.9 and 0.7 percentage points, respectively. On the other hand, an identical increase in cash flow would raise the probability of a given rating to be ranked A by 2.1 and 0.3 percentage points. Therefore, our findings are not only statistically but also economically important.

Overall, the baseline specification suggests that all explanatory variables are important in determining market implied ratings. We point out, however, that the baseline model ignores one important characteristic of the ratings process and the issuers that are rated. Specifically, the model does not allow for the distinction between "financially constrained" and "financially unconstrained" firms that has been shown to be significant factor in the relationship between firm characteristics and access to credit through bank lending and balance sheet channels, or the investment-agency cost literature. This distinction can be critically important since our explanatory variables have disproportionate effects for different types of firms classified by this criterion, as shown in Table 3. In the next sub-section, we interact dummies for constraints with our firm-specific financial variables to assess whether the financing constraint is a dimension which is taken into account by the credit ratings industry in its ratings methodology.

(ii) The Role of Financial Constraints

We now explore the impact of financial constraints on the response of the ratings to balance sheet characteristics as shown in equation (2). Therefore, comparing across columns in Table 5 allows us to investigate the specific influence of each measure of being constrained (based on the dividend payout ratio) on each of the financial variables in the rows.

Taking the leverage variable, *LEV*, we observe that although the estimated coefficients are consistently positive and significant for both constrained and unconstrained firms, they are larger for the former group of firms. The tests of equality suggest that the differences between the interacted coefficients are significant in both cases. This result highlights a key connection between the impact of leverage on the implied rating of the firm and the designation "financially constrained". For constrained firms, high leverage can be seen as a sign of a deteriorating balance sheet and therefore increases the probability of a lower rating. This result implies that for constrained firms, leverage issues become more acute than for their unconstrained counterparts. To ascertain the economic importance, let us consider the marginal effects for the coefficients on leverage for constrained and unconstrained firms. Taking the EQIR model we find that a 1% increase in leverage would reduce the probability of a given rating to be ranked A by 1.4 percentage points for constrained firms and by 1.1 percentage points for unconstrained firms. In the CDSIR model the corresponding marginal changes for constrained and unconstrained firms are 0.9 and 0.5, respectively.

Coverage ratio (*COV*) measures the extent to which cash flow is sufficient to pay for financial costs and therefore proxies for creditworthiness. The point estimates are systematically negative and significant only for unconstrained firms, while they are insignificant for the constrained group of firms. Constrained firms display a poorly determined coefficient due to the fact that their credit ratings may have already

Table 5
Financial Constraints and Market Implied Ratings

	EQIR (1)	*CDSIR (2)*
$LEV * CONS$	0.043***	0.039***
	(8.59)	(8.51)
$LEV * (1 - CONS)$	0.035***	0.023***
	(11.06)	(8.43)
$COV * CONS$	0.029	0.024
	(1.59)	(0.61)
$COV * (1 - CONS)$	−0.092**	−0.048***
	(−2.00)	(−3.32)
$LIQUID * CONS$	−0.020***	−0.010
	(−2.76)	(−1.55)
$LIQUID * (1 - CONS)$	−0.024***	−0.0001
	(−6.68)	(−0.11)
$CF * CONS$	−0.115***	−0.074***
	(−4.41)	(−3.02)
$CF * (1 - CONS)$	−0.036**	−0.009
	(−2.41)	(−0.69)
$PROF * CONS$	−0.082***	−0.069***
	(−5.82)	(−5.11)
$PROF * (1 - CONS)$	−0.001	−0.003
	(−0.05)	(−0.13)
$CONS$	0.550***	0.534***
	(3.78)	(4.15)
$SIZE$	−0.929***	−0.570***
	(−18.02)	(−14.18)
VOL	1.430***	0.819***
	(3.64)	(2.68)
$Observations$	1,124	1,121
$Pseudo - R^2$	0.41	0.27
Test of equality: *LEV*	0.07	0.00
Test of equality: *COV*	0.00	0.07
Test of equality: *LIQUID*	0.63	0.14
Test of equality: *CF*	0.00	0.01
Test of equality: *PROF*	0.00	0.01
Marginal effects when rating = A		
$LEV * CONS$	−1.41	−0.90
$LEV * (1 - CONS)$	−1.11	−0.53
$COV * CONS$	−3.08	−0.55
$COV * (1 - CONS)$	0.31	1.11
$LIQUID * CONS$	0.66	0.23
$LIQUID * (1 - CONS)$	0.79	0.007
$CF * CONS$	3.86	1.71
$CF * (1 - CONS)$	1.22	0.19
$PROF * CONS$	2.76	1.58
$PROF * (1 - CONS)$	0.003	0.07
$CONS$	−15.73	−11.55
$SIZE$	31.17	13.94
VOL	−48.01	−18.98

Notes:
The table presents ordered probit estimation results. $CONS$ is a dummy variable which takes the value one if the firm's dividend payout ratio is below the bottom 25th percentile of the distribution of the dividend payout ratio of all the firms in that particular industry and year, and zero otherwise. * significant at 10%; ** significant at 5%; *** significant at 1%. Also see notes to Tables 3 and 4.

incorporated the possibility of limited creditworthiness in their balance sheets.[18] As a result, ratings for constrained firms may show lower sensitivity to changes in creditworthiness than those of unconstrained firms. The marginal effects for the EQIR model suggest that increasing coverage by 1% would increase the probability of a given rating to be ranked A by 0.31 percentage points for the unconstrained group of firms. The analogous marginal change for the CDSIR model is 1.11.

Liquidity (*LIQ*) measures the cash from operations relative to liabilities. Comparing the estimated coefficients for liquidity, we observe that they are negative and significant for both types of firms when predicting EQIR, while they are insignificant when predicting CDSIR. This result implies that a high liquidity increases the probability of an investment grade rating for both types of firms, but we are unable to find significant differences between the interacted coefficients. We can conclude that in the CDSIR model, the coefficients on liquidity are poorly determined both for the constrained and unconstrained firms. On the other hand, liquidity is equally important for both constrained and unconstrained firms in predicting Equity implied ratings. The marginal changes for constrained and unconstrained firms when we focus on a single A equity implied rating are 0.66 and 0.79, respectively. When we look at the CDSIR model the marginal changes are 0.23 and 0.007 for constrained and unconstrained firms, respectively.

The influence of cash flow (*CF*) on the probability of being in each rating category measures the extent to which higher cash flows enables firms to be assigned a higher implied rating. This variable captures a firm's ability to generate resources. Cash flow has negative coefficients which are highly significant for constrained firms. For unconstrained firms we find that cash flow is negative in both models but significant only when predicting EQIR. According to the tests of equality, however, the coefficients for constrained and unconstrained firms are statistically different. In sum, we find that cash flow generation is an important determinant for constrained firms' implied ratings. This result is not only statistically, but also economically important. Specifically, a 1% increase in cash flow would raise the probability of a given Equity implied rating to be ranked A by 3.8 percentage points for constrained firms and by 1.2 percentage points for their unconstrained counterparts. An identical increase would raise the probability of a given CDS implied rating by 1.71 percentage points for constrained firms and by 0.19 percentage points for unconstrained firms.

Comparing the estimated coefficients for profitability (*PROF*), we observe that they are negative for both types of firms, but significant only for constrained firms. This result implies that high levels of profitability reduce the probability of being assigned a speculative grade rating for constrained firms only. On the other hand, profitability does not have any effect on unconstrained firms' probability of being assigned a speculative grade rating. The result that liquid, high-revenue generating firms with high levels of cash flow attract better ratings is consistent with evidence presented by other studies (Blume et al., 1998; and Amato and Furfine, 2004) in which firms with higher profits are more likely to improve their rating. The marginal changes for considering a single A rating, are 2.76 and 0.003 for constrained and

18 We noted earlier in Table 3 than unconstrained firms have substantially higher coverage ratios compared to their constrained counterparts.

Table 6
In-sample Predictions

	Predicted EQIR rating							
Actual EQIR rating	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*Total*
AAA	0	5	0	0	0	0	0	5
AA	0	26	28	0	0	0	0	54
A	0	4	275	97	1	0	0	377
BBB	0	0	86	256	54	0	0	396
BB	0	0	3	85	127	14	0	229
B	0	0	1	2	33	27	0	63
CCC	0	0	0	0	0	0	0	0
Total	0	35	393	440	215	41	0	1,124

	Predicted CDSIR rating							
Actual CDSIR rating	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*Total*
AAA	17	22	4	0	0	0	0	43
AA	9	39	56	36	1	0	0	141
A	2	34	84	112	6	0	0	238
BBB	0	9	62	227	43	5	0	346
BB	0	0	3	107	64	26	1	201
B	0	0	0	25	36	44	9	114
CCC	0	0	0	2	8	18	10	38
Total	28	104	209	509	158	93	20	1,121

Notes:
The table reports in-sample predictions for EQIR and CDSIR models. The leftmost column shows actual ratings while the right-hand side columns show the prediction of the ordered probit.

unconstrained firms in the EQIR model, while those for the CDSIR model are 1.58 and 0.07, respectively.[19]

In addition to the indirect effect of financing constraints (through interactions with financial variables) on the market implied ratings, we also allow for a direct effect. This effect is judged by the coefficient on the constraint dummy (*CONS*), which is positive and significant in both models. This result suggests that firms categorized as constrained are more likely to obtain a worse rating compared to unconstrained firms. Finally, both our control variables size and firm volatility remain highly significant and retain their expected signs as in the baseline model.

(iii) Model Predictions

(a) In-sample Predictions

Table 6 compares predicted versus actual ratings, using information from the estimated models in section (ii). Reading across each row gives the number of predicted observations per category against the actual outcome in the leftmost column. To

19 We find differences between the marginal effects of EQIR and CDSIR models. All the financial variables, with the exception of the coverage ratio, appear to be economically more important in predicting Equity implied ratings than CDS implied ratings. This result may indicate that Fitch puts more emphasis on the balance sheet information when they develop Equity implied ratings.

evaluate the predictive power of our model we employ two different statistics, *SC* and *CP*. We expect the former statistic to be influenced by any dominant outcome in the data, while the latter is corrected for this problem.

We begin by comparing results using the EQIR model shown in column (1) of Table 5. The predictive values are given in the upper panel of Table 6. We observe that the model correctly predicts AAA 0 times, AA 26 times, A 275 times, BBB 256 times, BB 127 times, B 27 times and CCC 0 times. There are 711 occasions when the correct prediction is made, hence we find that the $SC = 711/1{,}124$, which suggests that we have approximately 63.2% correct predictions. We then allow for the dominant outcome by reporting the Merton correct predictions statistic. This test calculates correct predictions using the proportion of correct predictions for each of the five rating categories: $CP_1 = 0/5$, $CP_2 = 26/54$, $CP_3 = 275/377$, $CP_4 = 256/396$, $CP_5 = 127/229$, $CP_6 = 27/63$ and $CP_7 = 0/0$. This test implies that $CP = 0.34$, which shows a lower but still reasonable predictive ability of our model.[20]

Our model predictions using the CDSIR are reported in the bottom panel of Table 6. We find that the proportion of correct predictions against the actual outcomes is $SC = 485/1{,}121$, indicating approximately 43% of predictions is correct. Comparing this statistic with the Merton correct prediction we find $CP = 0.26$. The results reveal that both EQIR and CDSIR models have good predictive ability.

(b) Out-of-sample Predictions

This section presents out-of-sample predictions of market implied ratings using the past and current information available up to time T. We use an expanding window method, which allows the successive observations to be included in the initial sample prior to forecast of the next one-step ahead prediction of the rating while keeping the start date of the sample fixed. By this method, we forecast future ratings $\hat{q}_{t+1}$, $\hat{q}_{t+2}$ etc. The first prediction date is year 2005 and we then increase T by one each time until T reaches year 2007.

The top panel of Table 7 shows the cross-tabulations of the predicted against observed outcomes using the EQIR model, while the bottom panel those for the CDSIR model. To begin with equity ratings, computing the *SC* statistic we get a figure of 0.66 and the Merton correct prediction measure indicates $CP = 0.52$. With respect to the CDSIR model, the proportion of correct predictions against the actual outcomes is $SC = 364/817$, indicating approximately 44% of predictions is correct. Finally, the Merton correct prediction measure indicates $CP = 0.30$. We conclude therefore that the predictive ability of both models is upheld when we conduct out-of-sample exercises.

6. ROBUSTNESS TESTS

(i) Alternative Specifications

In order to ensure that our results are not driven from the way that we split our sample, we use the 50th percentile as an alternative cut-off point. In particular, we

20 For instance, Amato and Furfine's (2004) model attains similar scores for the statistics, namely $SC = 0.52$ and $CP = 0.26$ for the model with time dummies.

Table 7
Out-of-sample Predictions

	Predicted EQIR rating							
Actual EQIR rating	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*Total*
AAA	0	1	0	0	0	0	0	1
AA	0	18	12	0	0	0	0	30
A	0	4	210	36	0	0	0	250
BBB	0	0	77	179	16	0	0	272
BB	0	0	2	77	93	7	0	179
B	0	0	1	1	30	21	0	53
CCC	0	0	0	0	0	0	0	0
Total	0	23	302	293	139	28	0	785
	Predicted CDSIR rating							
Actual CDSIR rating	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*Total*
AAA	14	12	3	0	0	0	0	29
AA	3	29	41	11	1	0	0	85
A	2	28	64	72	2	0	0	168
BBB	0	9	56	160	22	2	0	249
BB	0	0	3	89	49	16	1	158
B	0	0	0	21	27	39	8	95
CCC	0	0	0	2	7	15	9	33
Total	19	78	167	355	108	72	18	817

Notes:
The table reports out-of-sample predictions for EQIR and CDSIR models. The leftmost column shows actual ratings while the right-hand side columns show the prediction of the ordered probit.

define constrained firms as those whose dividend payout ratio is below the median of the distribution of the dividend payout ratio of all the firms in that particular industry and year, and zero otherwise. Next, we re-estimate the empirical models from Table 5 and report the results in columns (1) and (2) of Table 8. We are able to confirm that leverage, liquidity, cash flow and profitability are more important in predicting credit ratings for constrained firms, while the opposite is true for the coverage ratio. In addition, the differences between the interaction terms are statistically significant in most cases. Finally, we note that the coefficient on the financing constraint dummy remains positive and highly significant highlighting the direct influence of financial constraints on the probability of obtaining a credit rating. In summary, we can conclude that our main empirical results are robust to alternative cut-off values.

Next, we check whether other proxies for financing constraints can be used for robustness. First, we employ the firm's size and we create a dummy variable *Small*, which is equal to one if the firm's real total assets are below the bottom 25th percentile of the distribution of the size of all the firms in that particular industry and year, and zero otherwise.[21] Second, we rely on firms' bank dependency, as measured by the ratio of short-term debt to total debt. Therefore, we generate a dummy variable *BankDep*, which is equal to one if the firm's ratio of short-term debt to total debt is above the

21 Size is the key proxy for capital market access by manufacturing firms in Gertler and Gilchrist (1994) because small firms are more vulnerable to capital market imperfections and thus more likely to be financially constrained.

Table 8
Robustness Tests

	EQIR 50th perc (1)	*CDSIR 50th perc (2)*	*EQIR Small (3)*	*CDSIR Small (4)*	*EQIR Bankdep (5)*	*CDSIR Bankdep (6)*	*EQIR Spread (7)*	*CDSIR Spread (8)*
LEV ∗ CONS	0.039***	0.030***	0.048***	0.020***	0.045***	0.031***	0.038***	0.040***
	(11.06)	(9.49)	(9.74)	(5.46)	(10.90)	(10.25)	(6.98)	(7.57)
LEV ∗ (1−CONS)	0.032***	0.021***	0.039***	0.034***	0.042***	0.023***	0.035***	0.025***
	(8.41)	(6.95)	(10.66)	(9.97)	(7.26)	(4.74)	(9.03)	(7.96)
COV ∗ CONS	0.094***	−0.001	0.101***	−0.012	−0.008	−0.034***	0.098	0.132***
	(3.92)	(−0.03)	(3.27)	(−0.37)	(−0.41)	(−3.63)	(1.55)	(3.26)
COV ∗ (1−CONS)	−0.001	−0.065***	0.006	−0.049***	−0.073***	−0.072*	−0.004	−0.110***
	(−0.07)	(−3.89)	(0.36)	(−3.05)	(−3.39)	(−1.80)	(−0.23)	(−5.96)
LIQUID ∗ CONS	−0.028***	0.007**	−0.041***	−0.013**	−0.030***	−0.005	−0.027***	−0.009
	(−8.02)	(1.98)	(−8.31)	(−2.40)	(−7.01)	(−1.06)	(−2.71)	(−1.41)
LIQUID ∗ (1−CONS)	−0.016***	−0.005	−0.025***	0.002	−0.027***	−0.001	−0.023***	0.001
	(−3.40)	(−1.28)	(−4.64)	(0.56)	(−4.86)	(−0.18)	(−5.35)	(0.18)
CF ∗ CONS	−0.050***	−0.051***	−0.061***	−0.053**	−0.057*	−0.006	−0.122**	−0.057**
	(−2.82)	(−3.27)	(−3.52)	(−2.46)	(−1.95)	(−0.23)	(−2.57)	(−2.08)
CF ∗ (1−CONS)	−0.036*	0.018	−0.042**	−0.017	−0.051***	−0.020	−0.015	0.009
	(−1.90)	(1.16)	(−2.03)	(−1.26)	(−3.22)	(−1.58)	(−0.82)	(0.62)
PROF ∗ CONS	−0.087***	−0.077***	−0.124***	−0.084***	−0.119***	−0.082***	−0.085***	−0.070***
	(−4.88)	(−4.86)	(−5.92)	(−6.05)	(−7.66)	(−6.11)	(−4.50)	(−4.48)
PROF ∗ (1−CONS)	−0.056***	−0.035**	−0.082***	−0.034*	−0.067***	−0.070***	0.030	−0.026
	(−3.29)	(−2.26)	(−5.26)	(−1.75)	(−2.78)	(−2.89)	(0.59)	(−1.01)
CONS	0.314***	0.460***	0.165	0.063	0.141	0.162*	0.596***	0.183
	(2.70)	(4.59)	(0.95)	(0.44)	(1.57)	(1.95)	(3.21)	(1.04)
SIZE	−0.890***	−0.550***	−0.976***	−0.723***	−1.100***	−0.582***	−0.856***	−0.556***
	(−17.01)	(−13.63)	(−14.08)	(−13.86)	(−17.37)	(−14.30)	(−14.57)	(−11.07)
VOL	1.170***	0.705**	1.375***	0.852**	1.425***	0.678**		
	(3.15)	(2.35)	(2.99)	(2.72)	(3.21)	(2.25)		

Table 8
(Continued)

	EQIR *50th perc* *(1)*	*CDSIR* *50th perc* *(2)*	*EQIR* *Small* *(3)*	*CDSIR* *Small* *(4)*	*EQIR* *Bankdep* *(5)*	*CDSIR* *Bankdep* *(6)*	*EQIR* *Spread* *(7)*	*CDSIR* *Spread* *(8)*
CDS SPREAD							−0.0001	0.00002
							(−1.11)	(0.11)
Observations	1,124	1,121	1,124	1,121	1,124	1,121	756	746
$Pseudo - R^2$	0.41	0.27	0.49	0.29	0.49	0.29	0.31	0.31
Test of equality: *LEV*	0.08	0.00	0.21	0.00	0.28	0.07	0.53	0.00
Test of equality: *COV*	0.00	0.00	0.00	0.27	0.00	0.09	0.12	0.00
Test of equality: *LIQUID*	0.03	0.01	0.01	0.01	0.60	0.42	0.68	0.14
Test of equality: *CF*	0.53	0.00	0.44	0.13	0.84	0.35	0.03	0.02
Test of equality: *PROF*	0.16	0.03	0.05	0.01	0.03	0.61	0.02	0.09
Marginal effects when rating = A								
$LEV * CONS$	−1.26	−0.69	−1.51	−0.48	−1.27	−0.73	−1.25	−0.94
$LEV * (1 - CONS)$	−1.22	−0.55	−1.33	−0.84	−1.44	−0.54	−1.11	−0.59
$COV * CONS$	−3.09	0.46	−3.11	0.28	0.26	0.80	−2.80	−3.33
$COV * (1 - CONS)$	0.004	1.28	−0.19	1.11	2.35	1.71	0.14	2.66
$LIQUID * CONS$	0.85	−0.13	1.28	0.32	0.98	0.11	0.85	0.26
$LIQUID * (1 - CONS)$	0.65	0.004	0.77	−0.04	0.87	0.001	0.69	−0.002
$CF * CONS$	1.75	1.29	1.92	1.29	1.06	0.14	5.22	1.33
$CF * (1 - CONS)$	1.24	0.43	1.33	0.41	0.99	0.46	0.44	−0.32
$PROF * CONS$	2.86	2.56	3.89	2.05	2.22	1.96	2.97	1.61
$PROF * (1 - CONS)$	2.63	0.42	2.57	0.82	1.25	1.66	−2.37	0.67
CONS	−6.22	−7.69	−5.04	−1.52	−4.61	−3.86	−16.36	−3.25
SIZE	30.23	12.81	30.6	17.63	35.5	13.8	29.90	13.11
VOL	−39.18	−17.21	−43.2	−20.77	−45.97	−16.1		
CDS SPREAD							0.008	−0.001

Notes:
The table presents ordered probit estimation results. In columns (1) and (2) *CONS* is a dummy variable which takes the value one if the firm's dividend payout ratio is below the median of the distribution of the dividend payout ratio of all the firms in that particular industry and year, and zero otherwise. In columns (3) to (6) *CONS* indicates in turn *Small* and *Bank dependent* firms. *Small* is a dummy variable equal to one if the firm's real total assets are below the bottom 25th percentile of the distribution of the size of all the firms in that particular industry and year, and zero otherwise. *Bankdep*, is a dummy variable equal to one if the firm's ratio of short-term debt to total debt is above the top 25th percentile of the distribution of the short-term debt to total debt ratio of all the firms in that particular industry and year, and zero otherwise. In columns (7) and (8) *SPREAD* denotes 5-year CDS spread as an alternative measure of firm risk. * significant at 10%; ** significant at 5%; *** significant at 1%. Also see notes to Tables 3 and 4.

top 25th percentile of the distribution of the short-term debt to total debt ratio of all the firms in that particular industry and year, and zero otherwise.[22] We report the results in columns (3) to (6) of Table 8. Columns (3) and (4) refer to the size criterion, while columns (5) and (6) to the bank dependency criterion. We find that our main results are upheld. Specifically, leverage, liquidity and profitability are more significant in redicting ratings for constrained firms, while the opposite is true for coverage ratio. In sum, our results are robust to using alternative definitions of financing constraints.

Finally, in this sub-section we replace firm volatility with the CDS spread as a robustness check. The CDS spread assigns a precise figure on the risk the market attaches to firm default. For instance, taking the 5-year CDS spread, this risk is expressed as the percentage cost of insuring a firm's debt against default within 5 years. Data on the CDS spreads are taken from the Fitch database. These spreads are reported for several maturities, i.e., from 6 months to 10 years and they are expressed in basis points. In our analysis we take the 5-year CDS spreads, although our results were robust to an alternative selection. We report the results in columns (7) and (8) of Table 8. We continue to find that leverage, profitability and cash flow remain more important for constrained firms compared to unconstrained firms. We also observe one case where coverage ratio is more important for unconstrained firms. The CDS variable, which is meant to proxy for firm risk, is generally insignificant and poorly determined. We conclude that our results are not affected by replacing the firm volatility with the CDS spreads.

(ii) Alternative Estimation Methods

We now check the robustness of our results to alternative estimation methods. First, we employ the random effects ordered probit method to take into account the panel dimension of our dataset. The results for the random effects models are shown in columns (1) and (2) of Table 9. It is apparent that our results both quantitatively and qualitatively remain largely unchanged. We still find the estimated coefficients on leverage to be positive and highly significant for both types of firms, but they are significantly higher for firms classified as constrained only in the CDSIR model. Once again, we observe that the coverage ratio has a negative and significant coefficient for unconstrained firms as before, while liquidity and cash flow are negative for both types of firms. In addition, the coefficients on profitability are negative and significant for constrained firms in the EQIR model. We are able to find one case where the interacted coefficients are significantly different from each other. Taking these results into consideration, we can conclude that modeling market implied ratings using random effects methods does not make a substantial difference, suggesting that our results are not a by-product of not taking into account the unobserved heterogeneity.

We also use an instrumental variables technique to combat the potential endogeneity of our financial variables. According to Wooldridge (2010), the Rivers and Vuong (1988) approach can be extended to ordered probit models. Therefore, we instrument firm size and all financial variables using their own values lagged twice. Endogenous ordered probit results are reported in columns (3) and (4) of Table 9.

22 Firms that are more bank dependent are more likely to pay a higher external finance premium on bonds since they have a greater probability of bankruptcy, which can raise the cost of borrowing, and negatively affect the availability of credit.

Table 9
Alternative Estimation Methods

	EQIR-RE (1)	*CDSIR-RE* (2)	*EQIR-IV* (3)	*CDSIR-IV* (4)
$LEV * CONS$	0.046***	0.038***	0.037***	0.038***
	(6.19)	(5.27)	(4.41)	(4.44)
$LEV * (1 - CONS)$	0.040***	0.025***	0.032***	0.016***
	(7.88)	(4.57)	(5.89)	(3.53)
$COV * CONS$	0.096	0.101*	0.517**	0.493***
	(1.53)	(1.66)	(2.04)	(2.68)
$COV * (1 - CONS)$	−0.044*	−0.122***	−0.053**	−0.076***
	(−1.91)	(−6.15)	(−2.31)	(−3.78)
$LIQUID * CONS$	−0.036***	−0.006	−0.030	−0.024
	(−3.39)	(−0.67)	(−0.66)	(−1.33)
$LIQUID * (1 - CONS)$	−0.034***	−0.003	−0.029***	0.0001
	(−6.87)	(−0.73)	(−5.23)	(0.002)
$CF * CONS$	−0.097**	−0.084**	−0.250*	−0.193**
	(−2.34)	(−2.24)	(−1.91)	(−2.35)
$CF * (1 - CONS)$	−0.039**	−0.005	−0.069***	0.003
	(−2.12)	(−0.24)	(−2.82)	(0.15)
$PROF * CONS$	−0.088***	−0.030	−0.075***	−0.073***
	(−4.72)	(−1.56)	(−3.35)	(−3.62)
$PROF * (1 - CONS)$	0.006	0.047	0.147**	0.068
	(0.17)	(1.62)	(1.96)	(1.36)
$CONS$	0.556***	0.188	0.286*	0.260*
	(3.39)	(1.02)	(1.72)	(1.67)
$SIZE$	−1.021***	−0.514***	−1.006***	−0.590***
	(−11.89)	(−5.82)	(−17.92)	(−13.09)
VOL	1.588***	1.558***	1.375***	0.755**
	(3.24)	(3.56)	(3.13)	(2.32)
$Observations$	1,124	1,121	1,123	1,115
$Pseudo - R^2$			0.48	0.29
$Sargan$			0.583	0.100
$Anderson$			0.00	0.00
Test of equality: *LEV*	0.28	0.01	0.49	0.00
Test of equality: *COV*	0.40	0.00	0.06	0.00
Test of equality: *LIQUID*	0.78	0.72	0.97	0.17
Test of equality: *CF*	0.16	0.03	0.10	0.01
Test of equality: *PROF*	0.00	0.01	0.00	0.00
Marginal effects when rating = A				
$LEV * CONS$	−1.40	−0.86	−1.26	−0.89
$LEV * (1 - CONS)$	−1.23	−0.58	−1.08	−0.37
$COV * CONS$	−1.71	−0.56	−17.46	−11.65
$COV * (1 - CONS)$	1.12	1.91	1.77	1.80
$LIQUID * CONS$	0.81	0.20	1.01	0.57
$LIQUID * (1 - CONS)$	0.80	0.005	0.96	0.001
$CF * CONS$	2.51	1.91	8.43	4.56
$CF * (1 - CONS)$	0.66	0.09	2.32	−0.06
$PROF * CONS$	2.31	1.65	2.52	1.71
$PROF * (1 - CONS)$	−0.004	−0.05	−4.96	−1.60
$CONS$	−10.33	−5.41	−8.92	−6.01

Table 9
(Continued)

	EQIR-RE (1)	*CDSIR-RE* (2)	*EQIR-IV* (3)	*CDSIR-IV* (4)
$SIZE$	28.21	15.42	33.92	13.93
VOL	−37.65	−20.32	−46.33	−17.84

Notes:
Random-effect ordered probit regression results are reported in columns (1) and (2). Endogenous ordered probit regression results are reported in columns (3) and (4). In the endogenous ordered probit regressions leverage, coverage, liquidity, cash flow, profitability and size are instrumented using their lagged levels at time t 2. $CONS$ is a dummy variable which takes the value one if the firm's dividend payout ratio is below the bottom 25th percentile of the distribution of the dividend payout ratio of all the firms in that particular industry and year, and zero otherwise. The Sargan statistic is a test of the overidentifying restrictions, distributed as chi-square under the null of instrument validity. The Anderson canonical correlation statistic is distributed as chi-square under the null that the equation is unidentified. * significant at 10%; ** significant at 5%; *** significant at 1%. Also see notes to Tables 3 and 4.

The results for the interaction terms between the financial variables and the financing constraints dummies are generally consistent with those of Table 5. We find that both leverage and cash flow are more important in predicting CDS implied ratings for financially constrained firms than for unconstrained firms. One minor difference is related to the coverage ratio which now becomes positive and significant for the constrained group of firms in both models. This may suggest that improvements in creditworthiness do not have any positive effects on the rating, which may be due to constrained firms' generally bad financial shape. These firms have incurred additional payments to cover the entry cost in the bond market, given that underwriting fees would be larger in order to acquire and process their bonds.[23] In both models, the differences between the interacted terms are statistically significant. Moving to liquidity and profitability, we find that both variables enter with the expected negative signs but the differences between constrained and unconstrained firms are significant only for the latter variable. The constraint dummy on its own is positive and significant in both models confirming the direct influence of the dividend payout ratio on the determination of market implied ratings. Finally, the diagnostics do not indicate any problems regarding the choice and the relevance of our instruments. In sum, we conclude that our findings are robust to endogenous regressors.

(iii) Models with Lagged Rating Categories

In this sub-section, we test whether our main results are robust to estimating models that capture persistency by including lagged ratings categories.[24] The main advantage of a dynamic model is that it explicitly addresses the issue of persistence. Persistence is the causal link between the probability of obtaining a rating in year t and past

23 This is typically the case if the underwriter believes that they will be more likely to be left with a large inventory of unsold bonds.
24 There is a fast and growing literature which models ratings in a dynamic setting. For instance, Pagratis and Stringa (2009) show that bank ratings can be slow in responding to new information and therefore persistence appears to be very important in predicting bank ratings. In addition, Mizen and Tsoukas (2012a) show that using the persistence in ratings significantly improves the forecasts of default ratings assigned by the credit ratings agencies.

Table 10
Ordered Probit Models with Lagged Rating Categories

	EQIR (1)	*EQIR* (2)	*CDSIR* (3)	*CDSIR* (4)
$LEV * CONS$	0.029***	0.051***	0.024***	0.030***
	(5.48)	(5.17)	(4.62)	(6.13)
$LEV * (1 - CONS)$	0.025***	0.033***	0.017***	0.018***
	(7.57)	(5.91)	(4.95)	(5.69)
$COV * CONS$	0.057	0.105	0.091**	0.056
	(1.10)	(1.33)	(2.11)	(1.23)
$COV * (1 - CONS)$	−0.034**	0.034	−0.018	−0.018
	(−2.19)	(1.05)	(−1.27)	(−1.06)
$LIQUID * CONS$	−0.019***	−0.021***	−0.024***	−0.017**
	(−5.31)	(−3.26)	(−3.65)	(−2.20)
$LIQUID * (1 - CONS)$	−0.013**	−0.014	−0.006**	−0.005*
	(−1.97)	(−1.34)	(−2.14)	(−1.71)
$CF * CONS$	−0.072**	−0.156***	−0.044*	−0.050*
	(−2.51)	(−3.40)	(−1.67)	(−1.73)
$CF * (1 - CONS)$	−0.024	−0.012	0.004	0.013
	(−1.60)	(−0.47)	(0.32)	(1.01)
$PROF * CONS$	−0.067***	−0.084***	−0.064***	−0.075***
	(−4.92)	(−3.14)	(−4.86)	(−5.63)
$PROF * (1 - CONS)$	0.002	0.059	−0.032	−0.023
	(0.09)	(1.55)	(−1.15)	(−0.88)
$CONS$	0.315**	0.258	0.112	0.148
	(2.26)	(1.25)	(0.77)	(1.01)
$SIZE$	−0.633***	−0.582***	−0.435***	−0.362***
	(−10.89)	(−6.26)	(−9.68)	(−7.82)
VOL	1.207***	1.723***	0.810**	0.476
	(3.09)	(2.64)	(2.45)	(1.62)
AAA_1	−2.455***		−2.871***	
	(−3.37)		(−10.14)	
AA_1	−2.029***		−1.944***	
	(−7.93)		(−12.19)	
A_1	−0.975***		−1.087***	
	(−8.65)		(−9.83)	
BB_1	0.811***		0.935***	
	(6.91)		(8.15)	
B_1	1.564***		1.767***	
	(7.24)		(8.66)	
CCC_1			3.439***	
			(7.79)	
$AAA(1)$		−52.031***		−3.639***
		(−66.07)		(−11.16)
$AA(1)$		−34.675***		−2.152***
		(−57.75)		(−12.25)
$A(1)$		−17.791***		−1.032***
		(−47.21)		(−8.83)
$BB(1)\_1$		15.406***		1.076***
		(21.05)		(9.32)
$B(1)\_1$		0.457		1.825***
		(1.21)		(8.98)
$CCC(1)$				2.459***
				(7.10)

Table 10
(Continued)

	EQIR (1)	*EQIR* (2)	*CDSIR* (3)	*CDSIR* (4)
Observations	1,124	1,124	1,121	1,121
$Pseudo-R^2$	0.46	0.82	0.41	0.43
Test of equality: *LEV*	0.36	0.04	0.16	0.00
Test of equality: *COV*	0.66	0.37	0.01	0.10
Test of equality: *LIQUID*	0.41	0.55	0.00	0.12
Test of equality: *CF*	0.09	0.00	0.09	0.03
Test of equality: *PROF*	0.00	0.00	0.26	0.05
Marginal effects when rating = A				
$LEV * CONS$	−0.92	−1.91	−0.61	−0.77
$LEV * (1 - CONS)$	−0.79	−0.12	−0.45	−0.47
$COV * CONS$	−1.81	−0.39	−2.34	−1.45
$COV * (1 - CONS)$	1.10	−1.29	0.47	0.46
$LIQUID * CONS$	0.41	0.24	0.61	0.43
$LIQUID * (1 - CONS)$	0.59	0.005	0.14	0.12
$CF * CONS$	2.30	1.58	1.12	1.29
$CF * (1 - CONS)$	0.76	0.15	−0.10	−0.34
$PROF * CONS$	2.15	3.14	1.66	1.95
$PROF * (1 - CONS)$	−0.007	−0.66	0.81	0.60
CONS	−9.13	−2.18	−2.81	−3.72
SIZE	20.21	21.85	11.25	9.45
VOL	−38.54	−16.74	−20.93	−12.44

Notes:
The table presents ordered probit estimation results. The one period lags of the ratings are reported as AAA_1 etc. The initial period observations are reported as AAA (1) etc. *CONS* is a dummy variable which takes the value one if the firm's dividend payout ratio is below the bottom 25th percentile of the distribution of the dividend payout ratio of all the firms in that particular industry and year, and zero otherwise. * significant at 10%; ** significant at 5%; *** significant at 1%. Also see notes to Tables 3 and 4.

realizations of rating. The presence of persistence is typically tested by introducing lagged values of the dependent variable. Since we estimate a dynamic model we need to take account of the problem of initial conditions. This problem is due to the generic feature of the panel that firms (or individuals) inherit different unobserved and time-invariant characteristics which affect outcomes in every period. Thus, we estimate the model allowing for state dependence and accounting for the initial period ratings (Heckman, 1981; and Wooldridge, 2005).

The results of this exercise are shown in Table 10. In order to avoid potential multicollinearity problems we present two separate specifications: one containing the lagged ratings only, and the other only containing the initial period ratings. Our main findings are broadly confirmed. Specifically, we find significant differences for leverage between constrained and unconstrained firms when predicting equity and CDS implied ratings with initial period ratings. The interaction terms on liquidity do not suggest any important differences between the two types of firms, while cash flow and profitability are more important for the constrained group of firms. Moreover, both the lagged rating categories and the initial values appear to be important in predicting current ratings. A positive and significant coefficient on the lagged rating (relative to the baseline rating of BBB) means that the firm with this rating in the previous period is predicted to have a rating this period with a higher ordinal value than BBB this period. The opposite is true for negative coefficients. This suggests that persistence is important in market implied models although one would expect market implied ratings to be less prone to staleness.[25] Finally, we note that the pseudo R-squared improves substantially in both models suggesting a better of fit once persistence is controlled for with lagged rating categories and initial period ratings.

7. CONCLUSIONS

Recent financial volatility has drawn attention to credit rating agencies and their procedures, and many questions are being asked about the reliability of their ratings. The existing literature on ratings predictions has focused on the comparison between long-term agency ratings and market implied ratings. In this paper we introduce a new dimension, namely the firm-heterogeneity dimension in predicting market implied ratings. More specifically, we explore the impact of financial constraints on the response of the ratings to balance sheet characteristics. We show that financial variables have a differential impact on firm-types in predicting credit ratings, depending on whether firms are likely to face binding financing constraints. Our results, which are robust to considering additional measures of financing constraints, alternative cut-off points, employing an alternative measure of firm risk, and using alternative estimation methods, indicate that the financing constraint is an important dimension in the market implied ratings process.

Our findings are of relevance to managers, investors and rating agencies seeking to understand the mechanism through which financing constraints affect credit ratings. The results presented in this paper suggest that maintaining healthy balance sheets would substantially increase the probability of obtaining an improved rating. Thus, in good times firms should build up liquidity buffers which can be used during recessions, in order to maintain their ratings through the cycle. In addition, managers are advised to communicate managerial statements of liquidity to both investors and rating agencies effectively as a signal of their company's financial health.

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25 See Mizen and Tsoukas (2012a) for more details on the interpretation of lagged ratings and initial observations. Finally, note that there is a single observation for Equity implied ratings in the CCC category (see Table 1), which has been dropped in the estimation. Hence there are no estimated coefficients for this rating category.

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