Modelling market implied ratings using LASSO variable selection techniques[1]

by

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Abstract

Making accurate predictions of corporate credit ratings is a crucial issue to both investors and rating agencies. In this paper we investigate the determinants of market implied credit ratings in relation to financial factors, market-driven indicators and macroeconomic predictors. Applying a variable selection technique, the least absolute shrinkage and selection operator (LASSO), we document substantial predictive ability. In addition, when we compare our LASSO-selected models with the benchmark ordered probit model, we find that the former models have superior predictive power and outperform the latter model in all out-of-sample predictions.

Key words: Market implied ratings, LASSO, Financial ratios, Forecasting

JEL: G24, G33, C25, O16

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1. Introduction

In recent years, the growth of global credit market has been spectacular. From an investor's point of view, this has created new opportunities for higher returns and diversification but a careful management of credit risk is more necessary than ever. It is well known that the credit ratings of Moody's, Standard and Poor's, and Fitch play a key role in the pricing of credit risk and in the delineation of investment strategies since they measure the firm's long-term ability and willingness to meet debt servicing obligations. As such, the ratings indicate the probability that a given borrower will default. However, the accuracy and the timing of the ratings have been heavily criticized, especially during the most recent financial crisis. It has been argued that the standard agency ratings do not adjust quickly to price changes and therefore may be out of date. In response to these concerns, Fitch has recently developed a new model to derive Market Implied Ratings (MIRs) from bond and equity prices. The obvious advantage of these ratings compared to the conventional agency ratings is that they adjust instantaneously to price changes.

This study applies a variable selection approach, the least absolute shrinkage and selection operator (LASSO), and two of its most promising derivations, the Elastic net variable selection and the Penalized continuation ratio model, to the task of forecasting Fitch's CDS and Equity implied ratings (CDSIRs and EQIRs respectively hereafter). The research aims to exploit the LASSO properties and unveil the underlying structure of CDSIRs and EQIRs. There are several studies that use accounting ratios and other publicly available information in reduced-form models in order to predict credit ratings. These studies use various techniques (OLS, multinomial and ordered logit/probit models) to identify the most important characteristics for predicting bond ratings (see for instance the early studies by Poldue and Soldofsky, 1969, Pinches and Mingo, 1973, Kaplan and Urwitz, 1979 and Kao and Wu, 1990). The upshot is that financial healthiness is associated with ratings determination and prediction of default. Another line of research advocates the importance of estimating the models in a dynamic setting and documents a noticeable improvement in the predictive ability of the models once state dependence is controlled for (see Mizen and Tsoukas, 2012). One drawback of the reduced-form models, discussed above, is that they tend to employ many rating predictors as inputs despite the fact that only a sub-set is relevant. This has two critical implications. First, this approach can omit potentially important determinants leading to a decrease in prediction accuracy. Second, given the large number of predictors included, it does not provide a sparse representation, implying that these models cannot be readily used by market participants and rating agencies.

Our approach is mostly related to the literature that examines the determinants of credit ratings, but we add to it in two important ways. First, we make a methodological contribution by deriving a simple and more intuitive, yet innovative model, which is based on the variable selection technique, pioneered the by Tibshirani (1996)—the least absolute shrinkage and selection operator (LASSO). It is well accepted that this selection approach not only helps in identifying the most relevant predictors from an extensive set of candidate variables, but also improves the predictive power (see Fan and Li, 2001 and Tian et al, 2015). In addition, LASSO does not require strict assumptions such as a preselection of the variables considered and is consistent statistically as the number of observations approach infinity (Van de Geer 2008). Importantly, LASSO can potentially sidestep the problem of multicollinearity, which is fairly common in probit/logit models, and is computationally efficient even when considering a large set of potential predictors (Tian et al, 2015). Our study is the first, as far as we know, to provide a systematic empirical analysis of the LASSO selection technique in ratings forecasts. In doing so, we explore the relative importance of several time-varying covariates from an extensive set of firm-, market-specific and macro-economic explicators used to predict market implied ratings. This is important as we provide a parsimonious set of predictors that can be readily implemented by investors, managers and credit risk agencies.

Second, we use a data-set made up by market implied ratings instead of the standard long-term ratings. The former type of ratings represents an innovation to the ratings industry in an attempt to address the issue of staleness in their long-term counterparts. The market implied ratings rely on proprietary and data-intensive rating models that incorporate market information into a model-based credit assessment (see for instance, Rösch, 2005 and Tsoukas and Spaliara, 2014The most appealing characteristic of these ratings is that they have the ability to adjust instantly to market changes. Hence, we build on the foundations of the literature on implied (or point-in-time ratings) by investigating the forecasting power of models that capture volatile market changes.

To preview our findings, we show that several financial factors along with market-driven and macroeconomic variables contain information about market implied ratings. In addition, when applying the LASSO technique, we are able to significantly improve the forecasting power of our models in out-of-sample predictions compared to the ordered probit model, which is commonly adopted in the literature. In addition, we note that the LASSO BIC optimized models outperform their LASSO AIC counterparts for the dataset and periods under study.

The rest of the paper is laid out as follows. In section 2 we discuss the relevant literature. Section 3 presents the data and summary statistics. In section 4 we describe our methodology. In Section 5 we report the empirical results and robustness tests. Section 6 concludes the paper.

2. Related literature

The issue of how rating agencies use public information in setting quality ratings has attracted considerable attention in the literature. In fact, the literature goes as far back as Horrigan (1966). This study presents the first attempt to predict ratings based on the characteristics of the bonds and the issuing firms. The author concentrates on accounting data and financial ratios in order to find the most appropriate predictors. The set of preferred variables contains total assets, net worth to total debt, net operating profit to sales and working capital. Poldue and Soldofsky (1969) also assign ordinal numbers to ratings and investigate different accounting variables as potential determinants. They conclude that the most significant independent variables are long-term debt to total assets, the coefficient of variation of earnings, and total assets.[2] West (1970) challenged Horrigan's study by using another set of explanatory variables namely earnings volatility, capital structure, reliability and marketability. Based on values of the obtained R-squared, the author claims that the proposed model has a better explanatory power.

[2] The study shows that both profitability and coverage ratio are insignificant and quantitatively unimportant.

Pinches and Mingo (1973) adopt a two-stage approach to assign ratings to bond issues. This study attempts to test the predicting ability of a small number of explanatory variables using multiple regression and discriminant analysis. The proportion of correct predictions lie in the region of 70 percent. Moreover, Kaplan and Urwitz (1979) confirm the above studies by using an ordered probit analysis. They show that ratings may be reasonably well predicted using balance sheet information. Other studies that use a small number of explanatory variables (e.g leverage, profitability, interest coverage, firm's size and subordination status) to predict credit ratings include Ederigton (1985) and Gentry et al (1988). The former study uses long-term debt, subordination, total assets and interest coverage as explanatory variables, while the later focuses on subordination, size of issue, debt ratio, cumulative years that dividends were paid and net income to interest.

Blume, Lim, and MacKinlay (1998) depart from the traditional examination of credit ratings determinants by considering whether there is any tendency for a company that maintains the same values of accounting ratios over time to receive a lower rating due to worsening of rating standards. Using an ordered probit analysis they find that rating agencies have changed the way in which they evaluate credit standing and they report a secular tightening of rating agency standards. They conclude that it became more difficult for firms to obtain improved ratings in the mid-1980s and early 1990s.

More recently, ordered probit methodologies were employed by Hwang et al., 2009 and Hwang et al., 2010 to forecast credit ratings. Both studies show that several predictors are important in forecasting credit ratings such as the size of the company, balance sheet position, stock market performance and industry effects. In addition, modelling long-term ratings in a dynamic setting has shown improvements in forecasting (see Hwang, 2011 and Hwang, 2013). In a similar vein, Mizen and Tsoukas, 2012 find that allowing for persistence in ratings significantly improves the forecasting power of long-term ratings. In a subsequent study, Tsoukas and Spaliara, 2014 use the market implied ratings and the ordered probit modelling strategy to investigate the role of financial constraints. They conclude that financial variables are more important in predicting credit ratings for firms likely to face financing constraints.

The literature on market implied ratings has focused on the comparison between long-term agency ratings and market implied ratings. Breger et al. (2003) use bond spreads to find suitable thresholds categorizing bonds. They find that implied ratings are a superior application to identify default probability in the rating system. Rösch (2005) documents that implied ratings can provide more accurate default probability forecasts than long-term ratings. Castellano and Giacometti (2012) note that MIRs can be regarded as early warning signals of credit rating changes.

Moving to the line of work on variable selection techniques, there is only a handful of papers investigating default probabilities in various settings. Härdle and Prastyo (2013) employ the LASSO approach to predict default probability in a sub-set of Asian economies. Amendola et al, 2012 evaluate the default risk in the limited liability sector in Italy. Finally, Tian et al., 2015 evaluate the probability of bankruptcy using a comprehensive sample of US firms. The authors conclude that the accuracy in the out-of-sample prediction can be superior to previous studies of estimating default by combining reduced-form models with the LASSO procedure.

The studies discussed above provide a useful background on the credit ratings procedure and the selection process of relevant predictors. In the sections that follow we turn to our data and estimation strategy.

3. Data and summary statistics

3.1 Data sources

The data on market implied ratings are taken from Fitch's database and refer to solicited ratings for all traded US corporations. This database provides information on the CDS and Equity implied ratings assigned to each issuer as well as the date that the rating became available. Both CDS and Equity implied ratings are reported on a monthly frequency and span the period 2002 to 2008. In keeping with the normal practice in the literature, we categorize our firms into rating buckets without consideration of notches (i.e + or -). Amato and Furfine (2004) and Mizen and Tsoukas (2012), note that this classification takes into account large cumulative changes of ratings rather than small movements notch by notch, and avoids generation of rating categories with very few observations. Therefore 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-specific accounting data are extracted from Fitch's Peer Analysis Tool. Corporate historical data for all firms rated by Fitch are available on a quarterly basis from this database. For these firms with credit ratings, we link their ratings to Fitch's balance sheet statements and profit and loss accounts. Hence, our dataset is constructed by merging the monthly market implied ratings data and the quarterly firm-level accounting data. In other words, we have an entry for each firm-month with CDSIRs and EQIRs data and financial and market data. Following commonly used selection criteria in the literature; we exclude companies that do not have complete records on our explanatory variables and firm-months with negative sales and assets. To control for the potential influence of outliers, we winsorize the regression variables at the 1st and 99th percentiles.

Data on market indicators and macroeconomic variables are sourced from Bloomberg. These data items are reported on a monthly basis. Our combined sample contains data for 211 firms that operate in all sectors of the US economy except agriculture, forestry and fishing and public administration. The panel has an unbalanced structure with the number of observations on each firm varying between 1 and 63. Our sample presents two characteristics that make it especially appealing for our analysis. First, it includes both investment grade and high yield bonds, where previous studies mainly restricted their attention to investment grade bonds, neglecting the effects of speculative grade bonds. This is particularly beneficial since we are able to cover the entire spectrum of firms. 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 CDSIRs and the EQIRs databases can provide a representative base for conducting our empirical analysis.

3.2 Choice of explanatory variables

Prior empirical research on the determinants of credit ratings has considered both business and financial risks. The former type of risk includes an assessment of industry characteristics, firm size, management capability and organizational factors. The latter concerns the quality of a firm's accounting procedures, profitability, cash flow situation and its overall financial policy. In the market implied ratings, models typically consider market-related information in addition to the above mentioned factors. With that in our mind, we also turn to rating agencies and in particular to Fitch, to find out what matters when assigning a market implied rating. In other words, the selection of our explanatory variables is guided both from the existing empirical literature (see for example Kaplan and Urwitz, 1979; Ederington, 1985; Poon, 2003; Chava and Jarrow, 2004; Amendola et al, 2011; Mizen and Tsoukas, 2012; Hwang, 2013; Creal et al, 2014; Doumpos et al, 2015 and Tian et al, 2015), and the common practice of rating agencies (see Fitch 2007 and Liu et al. 2007).[3]

3.2.1 Firm-specific variables

We consider 16 firm-specific accounting variables as potential predictors of ratings. These variables are intended to measure different aspects of firms' financial health, these are size, leverage, coverage, cash flow, profitability and liquidity.[4] Specifically, we employ the firm size (DETA) as measured by the natural logarithm of firms' real total assets. Size accounts for the scale of the firm and would be expected to improve the rating. Next, we proxy leverage using a number of ratios: The ratio of long-term debt to total assets (LDA), the ratio of short-term debt to total assets (SDA), the ratio of total debt over total assets (TDA), the ratio of total assets over equity (AE), and the ratio of total debt to earnings before interest, taxes, depreciation, amortization, and restructuring or rent costs (TDEBITDA). Higher values of the above ratios are likely to increase financial risk and hence should worsen the rating. The next two measures capture the creditworthiness of the firm as they show the firm's ability to generate income in order to meet interest rate obligations: the ratio of earnings before interest and tax over interest expenses (EBITINT) and the ratio of total debt to earnings before interest, taxes, depreciation, amortization, and restructuring or rent costs to interest expenses (EBITDAINT). Both ratios would improve the credit rating if they were to increase. Further, cash flow is measured by the following ratios: Cash flow from operating activities over total assets (CFOA), and cash and equivalent over total assets (CASHEQA). We expect firms with higher cash flows to have improved ratings. The following five ratios measure firm

[3] The expected relationship between these variables and MIRs is presented in Table A1 in the Appendix.
[4] We provide a detailed description of the variables used in this study in Table A1 in the Appendix.

profitability: The ratio of operating income to net sales (OM), the ratio of net income without dividends over total capital (ROC), the ratio of net income over shareholders' equity (ROE), the ratio of net income over total assets (ROA) and the ratio of the funds from operations to total debt (FFD). An increase in the above mentioned profitability ratios should be associated with an improvement of ratings. Finally, liquidity is measured by the ratio of cash from operations to liabilities (LIQ), which indicates a firm's ability to satisfy its short-term obligations as they become due. Higher levels of liquidity should improve credit ratings.

3.2.2 Market-driven indicators

As noted above, market implied ratings are likely to be determined by market-related conditions. Therefore, we employ the following market indicators: Excess return (EXRET) as measured by the monthly stock return on the firm minus the S&P 500 index return. The relative size of a firm in market (RSIZE) measured by each firm's market equity value divided by the total market equity value. The above mentioned variables should be positively correlated with ratings upgrades. Next, we use the volatility of stock return (STD) which is calculated as the standard deviation of each company's monthly stock returns. We also use the systematic risk of each firm (Beta), measured by the Capital Asset Pricing Model for each firm. Finally, we extract the 1-year and 5-year default probabilities (PD1 and PD5) from the Fitch's Peer Analysis Tool. All three variables should worsen ratings if they were to increase.

3.2.3 Macroeconomic influences

We also consider an extensive list of macro-economic covariates as potential predictors of market implied ratings. Specifically, the stock market performance is evaluated by the S&P 500 return, which calculates returns on the S&P 500 index (RLSP). The short-term interest rate as measured by the three-month commercial paper rate (CPFFM), three-month Treasury bill rate minus federal funds rate (TB3) and the one-year constant maturity treasury rate (GS1). We also employ the general price level, as measured by the growth rate in the narrow money stock (MB) and inflation rate (INFL). The aggregate economic activity is captured by the rate of change in industrial production (DLIP), the index of the growth rate of real GDP (DLGDP), the average of monthly Chicago Fed National Activity Index over the year (CFNA), the average of monthly unemployment rate over the year (UNRATE) and the Chicago Board Options Exchange (CBOE) volatility index (VIX). All macro variables, with the exception of VIX, are reported in percentages. The eleven macroeconomic variables measure different aspects of the aggregate economy's performance. Their relationship with the market implied ratings could be either positive or negative as ratings tend to improve during good times but agencies have been observed to tighten their standards during these periods. Hence, the relationship between ratings and macro-economic variables is an issue that will be determined empirically.

3.3 Summary statistics

Tables 1 and 2 illustrate the distribution of firms by rating category for CDSIRs and EQIRs, respectively. It can be observed that the distribution of firms across the rating categories is quite stable and that most companies are assigned A and BBB ratings.

Insert Table 1

Insert Table 2

At the next stage, we report summary statistics for our explanatory variables in Tables 3 and 4. We present statistics splitting the sample between investment grade and sub-investment grade to gauge any differences across ratings categories. P-values for the tests of equality of means across the above mentioned groups are reported in the last columns of the tables. We observe, as expected, that firms in the investment grade group display better financial characteristics, as measured by the balance sheet indicators. The tests point to significant differences between the two groups, which indicate that there is a correlation between better financial health and an improved rating. Moving to the market indicators, we find that improved market conditions are associated with investment grade ratings, which also suggests a link between the market climate and the ratings.

Insert Table 3

Insert Table 4

4. Methodology

Our preferred framework to investigate forecasts of changes in market implied ratings is the LASSO modelling approach. The proposed methodology aims at selecting the most important predictors and at providing accurate MIRs forecasts. LASSO, originally proposed by Tibshirani (1996), is a form of an OLS regression which performs both variable selection and regularization through a shrinkage factor. It is capable of enhancing the accuracy and the interpretability of classical regression methods (Tibshirani, 1996). It is highly applicable in problems likes ours, where the number of predictors is larger than the number of observations and the underlying structure of the problem is unknown. It will help us unveil the relation between the potential predictors (at the firm and macro level) and identify their significance in predicting MIRs. A description of LASSO and the ordered probit model, which will act as benchmark in this study, follows.

4.1 LASSO framework

According to Tibshirani (1996), LASSO is a method of regression that enables estimation and variable selection simultaneously in the non-orthogonal setting. Under a suitable choice of penalty power, it forces the coefficients of non-relevant independent variables to shrink to zero in the regression while the coefficients of the more important predictors have less shrinkage. This reduces the variance of the predictive value and increases the accuracy of the regression estimations. Given a linear regression with standardized predictors and centred response values, LASSO resolves the l_1-penalized regression problem of estimating $\beta = \{\beta_i\}$ to minimize:

$$\sum_{i=1}^{N}(Y_{it} - \beta_1 X_{it} - \beta_2 X_{it-1} - \beta_3 X_{it-2} - \beta_4 X_{it-3} - \beta_5 W_{it} - \beta_6 W_{it-1} - \beta_7 W_{it-2} - \beta_8 W_{it-3} - \beta_9 Z_{it} - \beta_{10} Z_{it-1} - \beta_{11} Z_{it-2} - \beta_{12} Z_{it-3} - \delta Y_{it-1})^2 \,, subject\ to\ \sum_{j=1}^{p}\left|\beta_p\right| \leq s \quad (1)$$

This is the constrained form. It also can be written into Lagrangian form as:

$$\hat{\beta} = \arg min_{\beta} \left(\sum_{i=1}^{N}(Y_{it} - \beta_1 X_{it} - \beta_2 X_{it-1} - \beta_3 X_{it-2} - \beta_4 X_{it-3} - \beta_5 W_{it} - \beta_6 W_{it-1} - \beta_7 W_{it-2} - \beta_8 W_{it-3} - \beta_9 Z_{it} - \beta_{10} Z_{it-1} - \beta_{11} Z_{it-2} - \beta_{12} Z_{it-3} - \delta Y_{it-1})^2 + \lambda \sum_{j=1}^{p}\left|\beta_p\right|\right) \quad (2)$$

where $i = 1, 2, \ldots, N$ represents firms, $j = 1, 2 \ldots p$ indicates the survival number of predictors and $t = 1, 2, \ldots, T$ represents different time periods. In this context, t is the month end for monthly data. Different vectors β express the coefficients of relevant predictors to be estimated. Vector X accounts for 16 accounting variables, which can be divided into size, leverage, coverage, cash flow, profitability and liquidity. Vectors W and Z contain 6 market-driven variables and 11 macroeconomic variables, respectively. Following the literature (Güttler and Wahrenburg, 2007), all predictors are lagged three periods to mitigate potential time tendency. Y_{it-1} is an indicator of the firm's rating in the previous year and accounts for state dependence. All variables are chosen in line with previous related studies (Horrigan, 1966; Altman, 1968; Kaplan and Urwitz, 1979; Ohlson's, 1980; Ederington, 1985; Shumway, 2001; Duffie, Saita and Wang, 2007; Hwang, Cheng and Lee, 2009; Hwang, 2011; Mizen and Tsoukas, 2012; Hwang, 2013 and Tsoukas and Spaliara, 2014).

In equation (2), λ is called the tuning parameter. The process of selecting different values of λ can be regarded as the procedure of choosing the number of independent variables in LASSO. This is equivalent to minimizing the sum of squares with a constraint of the form$\sum|\beta_j| \le s$, where $s > 0$ is a user-specified parameter. As s decreases or λ increases in equations (1) and (2), the sum of absolute values of estimated coefficients is reduced and the shrinkage coefficients is achieved. If λ exceeds a threshold value or s is below a threshold value, respectively in corresponding models, some estimated coefficients would be equal to zero ultimately. This ‘‘L1 norm penalty’’ or the constraint formulation in LASSO can generate a more interpretable and sparse model.

As already noted, compared with other independent variable selection methods, LASSO can provide more stable and restricted models (Tibshirani, 1996; Fan and Li, 2001; Zou, 2006 and Tian et.al., 2015). It is also a computationally simple and efficient method (Efron et al., 2004). Several methods, such as cross validation and information criteria, have been proposed in selecting latent models with minimum prediction errors. Unfortunately, there is no formal theory or consensus on selecting the most appropriate method. In this study, AIC and BIC criteria (Schwartz, 1978) are used to detect the “best” model with the minimum prediction error among a series of candidate models.

4.2 Elastic net variable selection

Although LASSO is an efficient variable selection method, it suffers when the potential predictors are highly correlated with each other. In case of multi-collinearity, LASSO will keep only one from grouped predictors in the model. The remaining variables will not be highly correlated with the new residuals and thus they are likely to be excluded. However, more than one potential predictors might be important in a group. These variables are excluded and the LASSO performance deteriorates. LASSO is also sensitive when the number of predictors (p) is larger than the number of observations (n). In this scenario, LASSO limits the selected number of predictors and keeps at most n predictors in the model. Zou and Hastie

(2004) developed the Elastic net, a hybrid LASSO and ridge regression model that can deal with datasets where these two issues are present. The Elastic net allows "grouping" variables in the model by adding a l_2-penalty, where highly correlated predictors tend to be in (out) of the model together. Similar to LASSO, the Elastic net resolves the l_1-penalized and l_2-penalized regression problem of estimating $\beta = \{\beta_i\}$ to minimize:

$$\sum_{i=1}^{N}(Y_{it} - \beta_1 X_{it} - \beta_2 X_{it-1} - \beta_3 X_{it-2} - \beta_4 X_{it-3} - \beta_5 W_{it} - \beta_6 W_{it-1} - \beta_7 W_{it-2} - \beta_8 W_{it-3} - \beta_9 Z_{it} - \beta_{10} Z_{it-1} - \beta_{11} Z_{it-2} - \beta_{12} Z_{it-3} - \delta Y_{it-1})^2 \text{, } subject\ to\ \sum_{j=1}^{p}|\beta_p| \leq s_1, \sum_{j=1}^{p} {\beta_p}^2 \leq s_2 \quad (3)$$

The Lagrangian form is presented below:

$$\hat{\beta} = \arg min_\beta \left(\sum_{i=1}^{N}(Y_{it} - \beta_1 X_{it} - \beta_2 X_{it-1} - \beta_3 X_{it-2} - \beta_4 X_{it-3} - \beta_5 W_{it} - \beta_6 W_{it-1} - \beta_7 W_{it-2} - \beta_8 W_{it-3} - \beta_9 Z_{it} - \beta_{10} Z_{it-1} - \beta_{11} Z_{it-2} - \beta_{12} Z_{it-3} - \delta Y_{it-1})^2 + \lambda_1 \sum_{j=1}^{p}|\beta_p| + \lambda_2 \sum_{j=1}^{p} {\beta_p}^2\right) \quad (4)$$

Equations (3) and (4) are the vanilla version of Elastic net. The factor $\sum_{j=1}^{p} {\beta_p}^2 \leq s_2$ or $\lambda_2 \sum_{j=1}^{p} {\beta_p}^2$ allows correlated variables in the corresponding models. If s_1 is equal to positive infinite or λ_1 is set to 0, the Elastic net keeps the l_2-penalty in the model (ridge regression). However, if s_2 is equal to positive infinite or λ_2 is set to 0, the l_1-penalty will only be kept in the Elastic net and equations (3) and (4) reduce to simple LASSO. The l_2-norm constraint ensures a unique global minimum in the strictly convex loss function.

This property is beneficial in this study where several variables are subset of another (see for example, total debt over total assets and long-term debt to total assets). Similar to the simple LASSO, the AIC and BIC information criteria are employed to the task of selecting the model with the minimum prediction error.

4.3 Penalized continuation ratio model

The continuation ratio model estimates the probability of one particular category given the categories preceding this one. It is centred to the binary choice on each ordinal category, which provides the conditional probability of estimating categories. Fienberg (1980), Hardin and Hilbe (2007) and Long and Freese (2006) argue that the continuation ratio model is superior compared to the binary logistic regression. It is applicable in multi-classification problems where an individual can jump to the discrete rating category without having to pass the intermediate rating categories[5]. Similar to the binary logistic regression, the continuation ratio model creates binary choices on each ordinal category which allow the calculation of the relevant conditional probabilities. The conditional probability that an individual falls in a level, given that this individual has been in that level or beyond, is based on "conditional incremental thresholds". These cut-off points of categories can be controlled by users, implying that the estimated coefficients in the continuation ratio model are influenced by the direction chosen for modelling the response variable. In our work, the backward formulation of continuation ratio model of Archer and Williams (2012) is applied. The progression through the levels of MIRs from investment grade quality (AAA-BB) to sub-investment grade quality (BBB-CCC) is expressed by increasing integer values. This helps estimate the odds of lower MIRs rating compared with higher MIRs rating. The above can be expressed as:

$$\ln\left(P(Y_{it}=k)\big/P(Y_{it}\leq k)\right)=\alpha_k+\beta_1X_{it}+\beta_2X_{it-1}+\beta_3X_{it-2}+\beta_4X_{it-3}+\beta_5W_{it}+\beta_6W_{it-1}+\beta_7W_{it-2}+\beta_8W_{it-3}+\beta_9Z_{it}+\beta_{10}Z_{it-1}+\beta_{11}Z_{it-2}+\beta_{12}Z_{it-3}+\delta Y_{it-1} \qquad (5)$$

In equation (5), the dependent variable Y_{it} belongs to one ordinal rating categories $k = 1,\dots,K$. For each unit observation $i = 1,2,\dots n$, rather than modeling the response Y_{it} directly, each variable Y_{it} is equal to 1 if the response falls in category k ,and 0 otherwise. Thus, conditional likelihood is calculated as in multiple logistic regressions. Equation (5) has the same predictors as in equation (1). The above equation can be transformed into the following version to derive the conditional probability:

$$P(Y_{it}=k|Y_{it}\leq k)=e^{a}\big/(1+e^{b}) \qquad (6)$$

where

$a=\alpha_k+\beta_1X_{it}+\beta_2X_{it-1}+\beta_3X_{it-2}+\beta_4X_{it-3}+\beta_5W_{it}+\beta_6W_{it-1}+\beta_7W_{it-2}+\beta_8W_{it-3}+\beta_9Z_{it}+\beta_{10}Z_{it-1}+\beta_{11}Z_{it-2}+\beta_{12}Z_{it-3}+\delta Y_{it-1}$

and $b=\alpha_k+\beta_1X_{it}+\beta_2X_{it-1}+\beta_3X_{it-2}+\beta_4X_{it-3}+\beta_5W_{it}+\beta_6W_{it-1}+\beta_7W_{it-2}+\beta_8W_{it-3}+\beta_9Z_{it}+\beta_{10}Z_{it-1}+\beta_{11}Z_{it-2}+\beta_{12}Z_{it-3}+\delta Y_{it-1}$

The parameters can be estimated with maximum likelihood. This algorithm can be combined with LASSO and produce shrinkage coefficients that improve the model's predictive ability. The resultant model, a continuation ratio model where a l_1-penalized constraint is added, is the penalized continuation ratio model. The constrained form of the penalized continuation ratio model is:

[5] Market implied ratings share this property.

$$\hat{\beta} = \arg max_{\beta}(L(\alpha_k + \beta_1 X_{it} + \beta_2 X_{it-1} + \beta_3 X_{it-2} + \beta_4 X_{it-3} + \beta_5 W_{it} + \beta_6 W_{it-1} + \beta_7 W_{it-2} + \beta_8 W_{it-3} + \beta_9 Z_{it} + \beta_{10} Z_{it-1} + \beta_{11} Z_{it-2} + \beta_{12} Z_{it-3} + \delta Y_{it-1})), subject\ to\ \sum_{j=1}^{p} |\beta_p| \leq s_1 \quad (7)$$

In line with its LASSO counterparts, the AIC and the BIC criteria assist with selecting the best model.

4.4 The benchmark model

MIRs as a branch of credit ratings are discrete-valued signs and have an ordinal ranking. To meet the ordinal property of MIRs, the ordered probit model is applied as a benchmark model in the relevant literature (Kaplan and Urwitz, 1979; Gentry, 1988; Blume et al., 1998; Amato and Furfine, 2004 and Hwang et. al., 2009). Thus, in order to take into account both the existence of ordinal ranking and the difference between any two adjacent ratings, we follow the bulk of the literature by employing the ordered probit model as a benchmark. Specifically, we can define the categorical variable Y = 1, 2,.., 7 according to the rating assigned to each firm. We assume that there are is an unobservable dependent variable Y^* associated with Y. The relationship between Y and Y^* can be expressed as:

$$Y_{it}{}^* = \beta_1 X_{it} + \beta_2 X_{it-1} + \beta_3 X_{it-2} + \beta_4 X_{it-3} + \beta_5 W_{it} + \beta_6 W_{it-1} + \beta_7 W_{it-2} + \beta_8 W_{it-3} + \beta_9 Z_{it} + \beta_{10} Z_{it-1} + \beta_{11} Z_{it-2} + \beta_{12} Z_{it-3} + \delta Y_{it-1} + \varepsilon_{it} = x\beta + \varepsilon_{it} \quad (8)$$

$$Y_{it} = j\ if\ \alpha_{j-i} < Y_{it}{}^* \leq \alpha_j\ \ for\ j = 1, 2, \dots, 7, \quad (9)$$

X contains all explanatory variables and β expresses all estimated coefficients in equation (8). In equation (9), $\alpha_0 = -\infty, \alpha_7 = +\infty$ and α_j for j=1…6 are the unobservable cut-points with ascending orders into the interval scale. The error term ε_{it} is assumed to be a normally distributed residual with a zero mean and unit variance. Hence, the cumulative normal distribution can be linked to unobserved variable $Y_{it}{}^*$. If the j is the value between 2 and 6, the cumulative probability of variable Y_{it} can be described as:

$$\Pr(Y_{it} = j) = \Pr(\alpha_{j-1} < Y_{it}{}^* \leq \alpha_j) = \Phi[x\beta - \alpha_{j-1}] - \Phi[x\beta - \alpha_j] \quad (10)$$

where $\Phi(.)$ is the normal distribution function. If the j is equal to 1, the cumulative probability of variable Y_{it} can be stated as:

$$\Pr(Y_{it} = 1) = \Pr(Y_{it}{}^* \leq \alpha_1) = 1 - \Phi[x\beta - \alpha_1] \quad (11)$$

Similar to $j = 1$, if $j = 7$, the cumulative probability of variable Y_{it} can be calculated as

$$\Pr(Y_{it} = 7) = \Pr(Y_{it}{}^{*} > \alpha_6) = \Phi[x\beta - \alpha_6] \tag{12}$$

The unknown parameters can be evaluated by the maximum likelihood method. The likelihood function is expressed as: $L = \sum_i \ln[\Pr(Y_{it} = j)]$ for $j = 1, 2, \ldots, 7$.

5. Empirical results

5.1 Accuracy

In Table 5 we evaluate the forecasts of the models under study for firms' EQIRs and CDSIRs, using accuracy ratios. We report statistics for all candidate models for both in- and out-of-sample predictions. The former evaluation makes use of the first four years of the data (2002-2006), while the latter uses the remaining two years (2007-2008). In addition, we report at the foot of each panel the number of surviving variables.

Insert Table 5

To begin with the in-sample exercise, we find no notable differences between the competing models since they present a similar in-sample performance for both types of market implied ratings. Specifically, for EQIRs we find that the models have approximately 94% correct predictions. With respect to CDSIRs, approximately 89% predictions are correct. Moving to the out-of-sample prediction, the results suggest that the LASSO models clearly outperform their ordered probit benchmark. With reference to EQIRs, the percentage of correct predictions improves from 82% in the ordered probit model to 91% in the LASSO models. When considering the CDSIRs, our results indicate that the percentage of correct predictions increase from 24% in the ordered probit model to 85% in the LASSO models.

Next, we compare the within performance of the LASSO models, by considering alternative LASSO information sets. Starting with EQIRs, there is no significant difference in the accuracy ratios of the various LASSO candidate models. For CDSIRs, the BIC-based models provide more accurate out-of-sample forecasts compared to the AIC-based LASSO models. It is interesting to note that the BIC-based LASSO models select consistently a smaller number of predictors than their AIC counterparts. This does not seem to affect their forecasting performance for EQIRs but leads to more accurate predictions for CDSIRs. Tables B1 to B28 in Appendix B illustrate the contingency Tables of the predicted against the actual outcome both in- and out-of-sample results for the various models presented in Table 5.

5.2 Statistical significance

To evaluate the relative performance of the models presented in the sub-section above, we employ three statistics. This approach will help us test for the statistical significance of the forecasts and to further validate our main findings. We begin by computing the Diebold and Mariano (DM) (1995) statistic, which should provide us with information whether the difference between two forecasts from competing models is statistically significantly different from zero. The DM tests the null hypothesis of equal predictive accuracy between the forecasts of two models (model A vs model B). Under the null hypothesis the statistic has an asymptotic standard normal. A statistically significant DM statistic indicates that the forecasts of the first model (A) are different from those of the second model (B). As well as reporting the values for DM statistics, we also consider the modified version of this test statistic that corrects for its tendency to be over-sized in moderate samples. To do so, we compute the Harvey et. al. (HLN) (1997) statistic, which is calculated under the null hypothesis of equivalence in forecasting accuracy. The calculated statistics are compared to the critical values of the Student's *t*-distribution with *n*-1 degrees of freedom (where *n* is the size of the sample). Finally, we report the Model Confidence Set (MCS) of Hansen et. al. (2003). The MCS test directly generates the superior predictors from a full set of models given specific criteria and confidence levels through testing prediction errors. The procedure provides a random data-dependent set of best forecasting models, acknowledging the information limitations in the datasets. Hansen *et al.* (2011) argue that the more informative the data are, the fewer models are included in the MCS. In all three tests described above, the Mean Squared Error is applied as loss function. The realizations of the three tests in the out-of-sample exercise for both types of ratings are presented in Tables C1 to C5 in Appendix C.1.

For the CDSIRs, as can be seen from Tables C1 and C3 and the corresponding DB and the HLN statistics, there is evidence of a statistically significant difference between the ordered probit model, which is the benchmark model, and the LASSO models. For the EQIRs, the results, as shown in Tables C2 and C4, are less clear cut. Only the ordered probit model seems to provide statistically different forecasts that seem inferior to the LASSO algorithms. All three statistical tests are unable to distinguish a LASSO outperformer for the EQIRs. Finally, the MCS tests for CDSIRs, reported in Table C5, indicate that the LASSO and the Penalized Continuation Ratio models optimized through the BIC criterion provide superior forecasts. As for EQIRS, the MCS tests reveal that all LASSO models provide good forecasts at the 5% significance level.

5.3 Robustness tests

The findings of the previous Sections are further validated by carrying-out two robustness tests. In the first test we consider only investment grade ratings, while in the second check we remove the later part of the sample period to minimise the potential effect of the recent global financial crisis.

5.3.1 Investment grade ratings

The majority of the previous related literature studies employ data with investment grade ratings. However, as noted by Amato and Furfine (2004), restricting attention to one category is likely to induce selection bias. On the other hand, pooling together both categories may result in misspecification of our model if changes in financial and business risk have a different impact on creditworthiness across the groups of firms. Therefore, we drop all speculative grade ratings and re-estimate our models. The accuracy ratios are presented in Table 6 while the DB, HLN and MCS statistics are reported in Tables C5 to C10 in Appendix C.2.

Insert Table 6

The results in Table 6 and Appendix C.2 corroborate our main findings. In the in-sample forecast exercises, all models present similar performance. For the CDSIRs, both versions of the Penalized Continuation Ratio models provide more accurate forecasts. On the other hand, for EQIRs all LASSO models display better predictive performance than their ordered probit benchmark. To sum up, even when limiting our sample to investment grade ratings only, on out-of-sample evidence the LASSO models outperform the benchmark model.

5.3.2 Pre-crisis period

The preceding analysis has employed the full time period (2002 to 2008) which spans the onset of the global financial crisis. One could argue that the results are affected by the fact that ratings stability was challenged during this time period. Other things equal, one would expect that market implied ratings should be immune to this criticism, but to make sure that our results are not driven by crisis-related events, we remove the years 2007 and 2008. In this exercise, the in-sample spans from 2002 to 2005 while 2006 acts as the out-of-sample period. Table 7 presents the relevant accuracy ratios and Tables C11 to C15 in Appendix C.3 the realizations of the statistical tests in the restricted dataset.

Insert Table 7

We note that on in-sample evidence all models continue to display similar accuracy. In the out-of-sample evaluation, for the CDSIRs the Elastic net BIC algorithm joins the LASSO BIC and the Penalized BIC as outperformer. For the EQIRs, the performance is consistent with the previous exercises. All LASSO models present similar forecasts that are more accurate than the ones obtained from ordered probit model. In addition, it is interesting to note the performance of the ordered probit model in the pre-crisis dataset. In particular, its out-of-sample accuracy is considerably lower than the ones obtained in the full and the investment-grade ratings dataset.

5.4 Discussion

In the previous Sections, a forecasting exercise on CDSIRs and EQIRs prediction is presented. For both types of market implied ratings all models present similar in-sample accuracy. In the out-of-sample evaluation, for CDSIRs, we observe that the Penalized continuation ratio BIC model is outperforming in all datasets. It is worth mentioning that the same model is consistently selecting less predictors than its counterparts. This implies that the Penalized continuation ratio BIC model makes a more efficient use of the underlying dataset. The remaining BIC models generate good forecasts that are in most cases more accurate than their AIC counterparts. For the EQIRs, in all cases the LASSO models outperform the ordered probit benchmark. The accuracy ratios of the BIC models are better but this difference is not statistically significant based on the DB, HLN and MCS statistics.

To sum up, we note that the LASSO models are able to provide more accurate out-of-sample forecasts on the CDSIRs and EQIRs ratings that outperform the ordered probit model. This is of particular interest given that the ordered probit model dominates the related literature in predicting credit ratings. From the LASSO models under study, the BIC optimized models seem able to provide better forecasts while at the same time they use less predictors. These results are robust to restricting the dataset to investment grade ratings and to removing the financial crisis years from the sample.

6. Conclusion

The ability to predict credit ratings within a reasonable margin of accuracy is of vital importance for both market participants and rating agencies. The focus on market implied ratings is even more justified as long-term ratings have been heavily criticized about their performance during the recent global financial crisis. We model the prediction of market implied ratings applying a variable selection technique, the least absolute shrinkage and selection operator (LASSO). Two of the most promising LASSO variants, the Elastic net and the Penalized continuation ratio model are also explored. All LASSO models select the most relevant predictors from a set of 136 variables and forecast the MIRs for a period of six years (2002 to 2008). This marks a break with the existing literature which typically relies on discrete limited dependent variable models.

Our results using monthly data from the US offer several interesting results. First, we show that several financial factors along with market-driven and macroeconomic variables contain information about market implied ratings. Second, the LASSO models perform better in out-of-sample prediction that do ordered probit models, mostly adopted in previous studies. Finally, the LASSO BIC optimized models outperform their LASSO AIC counterparts for the dataset and periods under study.

These results should go further in convincing risk managers and academics to explore variable selection models when assessing credit risk. The structure of credit ratings is unknown and likely to vary through time. Limited dependent variable models require a-priori knowledge on the dependent variables set, which can lead to misspecifications. On the other hand, variable selection models such as LASSO, are more flexible and can unveil the underlying structure of the problem leading to superior estimations and improved predictive ability.

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Table 1 CDSIRs by year

	AAA	AA	A	BBB	BB	B	CCC	Number of Observations
2002	4	35	46	32	20	1	0	138
2003	10	44	68	65	32	7	0	226
2004	11	41	60	70	35	10	0	227
2005	9	34	57	71	29	10	1	211
2006	9	24	52	63	26	4	1	179
2007	14	45	54	63	28	13	6	223
2008	12	19	13	33	13	3	1	94
Number of Observations	69	242	350	397	183	48	9	1298

Notes: The table presents the distribution of CDSIRs by year.

Table 2 EQIRs by year

	AAA	AA	A	BBB	BB	B	CCC	Number of Observations
2002	1	13	55	103	76	16	0	264
2003	2	19	91	106	43	5	0	266
2004	1	20	100	99	42	6	0	268
2005	0	10	70	87	38	4	0	209
2006	0	11	80	74	29	4	0	198
2007	1	19	91	80	41	8	0	240
2008	0	5	29	37	23	1	0	95
Number of Observations	5	97	516	586	292	44	0	1540

Notes: The table presents the distribution of EQIRs by year.

Table 3 Descriptive statistics-CDSIRs

Variable	Mean	Standard Deviation	Minimum	Maximum	p-value
	(1)	(2)	(3)	(4)	(5)
DETA					
Investment grade	9.6388	1.0132	7.2272	12.2084	
Non-investment grade	8.9536	0.9959	6.2539	12.2087	0.0000
AE					
Investment grade	3.2256	3.6336	1.3324	73.7340	
Non-investment grade	5.0224	8.8729	1.3283	123.5602	0.0000
LDA					
Investment grade	20.2416	11.2733	0.0000	79.3983	
Non-investment grade	30.1868	19.4641	0.0000	110.4453	0.0000
SDA					
Investment grade	3.5941	3.9838	0.0000	23.5410	
Non-investment grade	3.2961	4.1573	0.0000	23.4635	0.0000
TDA					
Investment grade	24.3546	11.9238	1.3017	87.0595	
Non-investment grade	37.4629	20.8746	0.6518	126.8760	0.0000
TDEBITDA					
Investment grade	2.3395	1.2107	0.3200	19.6400	
Non-investment grade	4.1208	2.8918	0.3200	23.0700	0.0000
EBITINT					
Investment grade	13.3805	19.0270	0.1541	209.3023	
Non-investment grade	7.2685	15.2730	0.1248	210.4054	0.0000
EBITDAINT					
Investment grade	16.0444	21.9950	0.6500	235.4000	
Non-investment grade	9.0872	14.5213	0.3100	196.7000	0.0000
CFOA					
Investment grade	6.9186	6.2625	-41.0623	38.4372	
Non-investment grade	7.1077	7.2097	-13.4106	65.9955	0.0000
CASHEQA					
Investment grade	8.6116	9.6531	0.0238	71.8277	
Non-investment grade	6.5258	8.1009	0.0030	64.0272	0.0000
OM					
Investment grade	13.9496	9.7304	-13.5155	53.0189	
Non-investment grade	10.3893	9.9617	-20.2276	52.6046	0.0000
ROC					
Investment grade	3.7919	5.3598	-34.1330	35.7771	
Non-investment grade	2.1389	7.0866	-36.3880	34.5209	0.0000
ROE					
Investment grade	12.5162	35.3349	-361.1511	452.2565	0.0000

Non-investment grade	9.5597	46.9441	-359.7868	516.7883	
ROA					
Investment grade	3.9430	4.4180	-26.4074	22.0518	
Non-investment grade	2.5165	5.5633	-23.8888	23.2336	0.0000
FFD					
Investment grade	40.7412	32.5483	-16.2800	267.1700	
Non-investment grade	24.4291	26.0776	-17.8000	225.3200	0.0000
LIQ					
Investment grades	12.02064	10.94679	-13.3151	59.8763	
Non-investment grade	11.55889	12.65565	-13.56745	62.18169	0.0000
EXRET					
Investment grade	0.0117	0.0646	-0.3525	0.4527	
Non-investment grade	0.0195	0.1108	-0.3526	0.4673	0.0149**
RSIZE					
Investment grade	0.2170	0.2641	0.0103	1.7570	
Non-investment grade	0.1107	0.1812	0.0041	1.7495	0.0000
STD					
Investment grade	0.0159	0.0079	0.0041	0.1134	
Non-investment grade	0.0256	0.0151	0.0041	0.1141	0.0000
BETA					
Investment grade	0.9366	0.6368	-0.8663	4.4144	
Non-investment grade	1.0795	0.9672	-0.8799	4.9196	0.0000
PD1					
Investment grade	24.0820	70.0007	2.0000	3000.0000	
Non-investment grade	162.7669	489.4410	2.0000	3000.0000	0.0000
PD5					
Investment grade	260.5300	310.3217	14.0000	4495.0000	
Non-investment grade	793.0404	907.6053	14.0000	5464.0000	0.0000

Notes: The Table reports the summary statistics of the explanatory variables used in the empirical models. Column 5 reports the p-value for the test of equality of means between the investment grade and non-investment grade categories. Investment grade refers to ratings from AAA to BBB. Non-investment grade refers to ratings BB and below. A detailed description of the variables used in this study is given in Table A1 in the Appendix.

Table 4 Descriptive statistics-EQIRs

Variable	Mean	Standard Deviation	Minimum	Maximum	p-value
	(1)	(2)	(3)	(4)	(5)
DETA					
Investment grade	9.5314	1.0515	7.0031	12.2084	
Non-investment grade	8.8701	0.9461	6.2539	12.2087	0.0000
AE					
Investment grade	3.4552	4.7315	1.3283	116.1204	
Non-investment grade	5.3173	9.3934	1.3283	123.5602	0.0000
LDA					
Investment grade	20.9162	12.5949	0.0000	110.1548	
Non-investment grade	32.5301	19.9743	0.0000	110.4453	0.0000
SDA					
Investment grade	3.7397	4.1512	0.0000	23.5410	
Non-investment grade	3.0151	3.9714	0.0000	23.4635	0.0000
TDA					
Investment grade	25.3924	13.5320	1.3017	126.8209	
Non-investment grade	40.3718	21.1606	0.6518	126.8760	0.0000
TDEBITDA					
Investment grade	2.5062	1.4809	0.3200	20.4000	
Non-investment grade	4.4812	3.0369	0.3200	23.0700	0.0000
EBITINT					
Investment grade	13.2588	20.3637	0.1601	210.4054	
Non-investment grade	5.3897	10.2101	0.1248	157.3792	0.0000
EBITDAINT					
Investment grade	15.7294	21.3681	0.4100	235.4000	
Non-investment grade	7.2437	11.9978	0.3100	171.8000	0.0000
CFOA					
Investment grade	7.8973	6.5051	-41.0623	40.5546	
Non-investment grade	5.9413	7.0742	-41.0623	65.9955	0.0000
CASHEQA					
Investment grade	8.6834	9.6845	0.0030	71.8277	
Non-investment grade	5.7724	7.3325	0.0033	58.4741	0.0000
OM					
Investment grade	13.0445	9.5560	-16.9133	53.0189	
Non-investment grade	10.3826	10.3917	-20.2276	52.5504	0.0000
ROC					
Investment grade	3.8570	5.6971	-35.0754	35.7771	
Non-investment grade	1.5077	7.1322	-36.3880	34.5140	0.0000
ROE					
Investment grade	13.3395	36.3731	-361.1511	473.0769	
Non-investment grade	7.5924	48.9666	-359.7868	516.7883	0.0000
ROA					
Investment grade	4.1096	4.6843	-26.4074	23.2190	
Non-investment grade	1.8536	5.4585	-26.4074	23.2336	0.0000
FFD					
Investment grade	38.8160	31.7571	-16.2800	267.1700	
Non-investment grade	21.6264	24.5682	-17.8000	224.0300	0.0000
LIQ					
Investment grade	13.5432	11.8937	-13.5675	62.1817	
Non-investment grade	9.495881	11.69661	-13.56745	57.22284	0.0000
EXRET					
Investment grade	0.0140	0.0723	-0.3525	0.4648	
Non-investment grade	0.0181	0.1089	-0.3526	0.4673	0.5831

RSIZE					
Investment grade	0.2047	0.2687	0.0088	1.7570	
Non-investment grade	0.0922	0.1307	0.0041	1.6261	0.0000
STD					
Investment grade	0.0172	0.0085	0.0041	0.1134	
Non-investment grade	0.0250	0.0155	0.0041	0.1141	0.0000
BETA					
Investment grade	0.9081	0.7224	-0.8757	4.8848	
Non-investment grade	1.1028	0.9284	-0.8799	4.9196	0.0000
PD1					
Investment grade	24.1369	54.1782	2.0000	3000.0000	
Non-investment grade	215.5352	567.0797	2.0000	3000.0000	0.0000
PD5					
Investment grade	250.8945	299.6934	14.0000	4495.0000	
Non-investment grade	1010.6400	970.2219	17.0000	5464.0000	0.0000

Notes: The Table reports the summary statistics of the explanatory variables used in the empirical models. Column 5 reports the p-value for the test of equality of means between the investment grade and non-investment grade categories. Investment grade refers to ratings from AAA to BBB. Non-investment grade refers to ratings BB and below. A detailed description of the variables used in this study is given in Table A1 in the Appendix.

Table 5. Accuracy Ratios and selected variables

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
EQIRs	In-sample prediction	0.9466%	0.9428%	0.9420%	0.9428%	0.9420%	0.9422%	0.9422%
	Out-of-sample prediction	0.823%	0.904%	0.906%	0.904%	0.907%	0.908%	0.908%
	Surviving variables	136	107	71	114	83	50	42
CDSIRs	In-sample prediction	0.8994%	0.8973%	0.8942%	0.8738%	0.8937%	0.8960%	0.8714%
	Out-of-sample prediction	0.241%	0.472%	0.849%	0.473%	0.845%	0.838%	0.856%
	Surviving variables	136	107	76	115	68	116	54

Notes: The Table reports the accuracy ratios and the number of independent variables for each model under study.

Table 6. Accuracy ratios and selected variables (investment-grade ratings)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
CDSIRs	In-sample prediction	0.899%	0.895%	0.897%	0.894%	0.897%	0.895%	0.893%
	Out-of-sample prediction	0.668%	0.849%	0.843%	0.849%	0.843%	0.866%	0.870%
	Surviving variables	134	87	50	91	52	53	44
EQIRs	In-sample prediction	0.952%	0.944%	0.943%	0.944%	0.943%	0.952%	0.948%
	Out-of-sample prediction	0.533%	0.921%	0.919%	0.921%	0.920%	0.919%	0.924%
	Surviving variables	134	102	71	110	73	86	50

Notes: The Table reports the accuracy ratios and the number of independent variables for each model under study.

Table 7. Accuracy ratios and selected variables (pre-crisis sample)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
CDSIRs	In-sample prediction	0.892%	0.894%	0.889%	0.893%	0.887%	0.893%	0.889%
	Out-of-sample prediction	0.122%	0.860%	0.919%	0.864%	0.919%	0.829%	0.918%
	Surviving variables	136	112	66	112	68	102	66
EQIRs	In-sample prediction	0.946%	0.943%	0.942%	0.943%	0.942%	0.942%	0.942%
	Out-of-sample prediction	0.165%	0.944%	0.944%	0.876%	0.944%	0.941%	0.941%
	Surviving variables	136	109	71	110	74	47	45

Notes: The Table reports the accuracy ratios and the number of independent variables for each model under study.

Appendix A

Table A1: Expected signs and variables definition

Covariates	Predicted relationship	Definition
Size		
DETA	+	Logarithm of real total assets
Leverage		
AE	-	Total assets/Equity
LDA	-	Long-term debt/Total assets
SDA	-	Short-term debt/Total assets
TDA	-	Total debt/Total assets
TDEBITDA	-	Total debt/Earnings before interest, taxes, depreciation, amortization, and restructuring or rent costs
Coverage		
EBITINT	+	Earnings before interest and tax/Interest expenses
EBITDAINT	+	Total debt/earnings before interest, taxes, depreciation, amortization, and restructuring or rent costs/Interest expenses
Cash flow		
CFOA	+	Cash flow from operating activities/Total assets
CASHEQA	+	Cash and equivalent/Total assets
Profitability		
OM	+	Operating income/Net sales
ROC	+	Net income less dividends/Total capital
ROE	+	Net income/Shareholders' equity
ROA	+	Net income/Total assets
FFD	+	Funds from operations/Total debt
Liquidity		
LIQ	+	Cash from operations/Liabilities
Market-driven Variables		
EXRET	+	Monthly stock return-the S&P 500 index return
RSIZE	+	Firm equity value/Total market equity value
STA	-	The standard deviation of a company's monthly stock returns
BETA	-	Systematic risk in the Capital Asset Pricing Model
PD1	-	1-year default probability
PD5	-	5-year default probability
Macroeconomic Variables		
RLSP	~	Return on S&P 500 index
CPFFM	~	3-month commercial paper rate
TB3	~	3-month Treasury bill rate minus federal funds rate
GS1	~	1-year constant maturity treasury rate
MB	~	Growth rate in the narrow money stock
INFL	~	Inflation rate
DLIP	~	Rate of change in industrial production
DLGDP	~	Real GDP growth
CFNA	~	Average Chicago Fed National Activity Index
UNRATE	~	Average unemployment rate
VIX	~	The Chicago Board Options Exchange volatility index

Notes: "+" indicates that the Market Implied Ratings would improve if the covariates rise. "-" indicates that the Market Implied Ratings would worsen if the covariates rise. "~" indicates uncertainty in the sign.

Appendix B

We cross tabulate predicted against observed CDSIRs outcomes in contingency Tables B1 to B7 for the in-sample prediction.

Table B1: In-sample Prediction in Ordered probit model in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	55	178	1	0	0	0	0	234
AA	42	871	69	13	0	0	0	995
A	0	46	1591	68	0	0	0	1705
BBB	0	2	66	1802	25	0	0	1895
BB	0	0	0	52	782	7	0	841
B	0	0	0	0	11	137	0	148
Below C	0	0	0	0	0	6	1	7
Total	97	1097	1727	1935	818	150	1	5825

Accuracy ratio=0.8994

Table B2: In-sample Prediction in LASSO_AIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	17	216	1	0	0	0	0	234
AA	10	901	68	16	0	0	0	995
A	0	42	1584	79	0	0	0	1705
BBB	0	0	64	1809	22	0	0	1895
BB	0	0	0	55	779	7	0	841
B	0	0	0	0	11	137	0	148
Below C	0	0	0	0	0	7	0	7
Total	27	1159	1717	1959	812	151	0	5825

Accuracy ratio=0.8973

Table B3: In-sample Prediction in LASSO_BIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	5	228	1	0	0	0	0	234
AA	3	908	57	27	0	0	0	995
A	0	41	1567	97	0	0	0	1705
BBB	0	0	60	1813	22	0	0	1895
BB	0	0	0	55	779	7	0	841
B	0	0	0	0	11	137	0	148
Below C	0	0	0	0	0	7	0	7
Total	8	1177	1685	1992	812	151	0	5825

Accuracy ratio=0.8942

Table B4: In-sample Prediction in Elastic net_AIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	17	216	1	0	0	0	0	234
AA	10	901	68	16	0	0	0	995
A	0	42	1584	79	0	0	0	1705
BBB	0	0	64	1809	22	0	0	1895
BB	0	0	0	55	779	7	0	841
B	0	0	0	11	137	0	0	148
Below C	0	0	0	0	0	7	0	7
Total	27	1159	1717	1970	938	14	0	5825

Accuracy ratio=0.8738

Table B5: In-sample Prediction in Elastic net_BIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	2	231	1	0	0	0	0	234
AA	4	907	56	28	0	0	0	995
A	0	41	1568	96	0	0	0	1705
BBB	0	0	60	1813	22	0	0	1895
BB	0	0	0	55	779	7	0	841
B	0	0	0	0	11	137	0	148
Below C	0	0	0	0	0	7	0	7
Total	6	1179	1685	1992	812	151	0	5825

Accuracy ratio=0.8937

Table B6: In-sample Prediction in Penalized continuation ratio model_AIC in CDSIRs

	Predicted CDS ratings							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	49	184	1	0	0	0	0	234
AA	40	871	69	15	0	0	0	995
A	0	43	1573	89	0	0	0	1705
BBB	0	0	62	1811	22	0	0	1895
BB	0	0	0	55	779	7	0	841
B	0	0	0	0	11	136	1	148
Below C	0	0	0	0	0	7	0	7
Total	89	1098	1705	1970	812	150	1	5825

Accuracy ratio=0.8960

Table B7: In-sample Prediction in Penalized continuation ratio model _BIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	21	212	1	0	0	0	0	234
AA	17	894	59	25	0	0	0	995
A	0	41	1569	95	0	0	0	1705
BBB	0	0	60	1813	22	0	0	1895
BB	0	0	0	55	779	7	0	841
B	0	0	0	11	137	0	0	148
Below C	0	0	0	0	0	7	0	7
Total	38	1147	1689	1999	938	14	0	5825

Accuracy ratio=0.8714

We cross tabulate predicted against observed CDSIRs outcomes in contingency Tables B8 to B14 for the out-of-sample prediction.

Table B8: Out-of-sample Prediction in Ordered Probit model in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	13	11	3	9	35	2	11	84
AA	44	43	31	33	43	21	19	234
A	1	56	57	38	19	61	14	246
BBB	0	1	58	86	40	70	100	355
BB	0	0	0	16	44	8	69	137
B	0	0	0	0	9	11	32	52
Below C	0	0	0	0	0	4	19	23
Total	58	111	149	182	190	177	264	1131

Accuracy ratio=0.2414

Table B9: Out-of-sample Prediction in LASSO_AIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	1	29	54	0	0	0	0	84
AA	111	110	12	1	0	0	0	234
A	0	2	153	82	9	0	0	246
BBB	0	0	5	171	167	12	0	355
BB	0	0	0	2	60	71	4	137
B	0	0	0	0	1	23	28	52
Below C	0	0	0	0	0	7	16	23
Total	112	141	224	256	237	113	48	1131

Accuracy ratio=0.4721

Table B10: Out-of-sample Prediction in LASSO_BIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	1	83	0	0	0	0	0	84
AA	0	212	22	0	0	0	0	234
A	0	12	224	10	0	0	0	246
BBB	0	0	12	340	3	0	0	355
BB	0	0	0	5	132	0	0	137
B	0	0	0	0	4	48	0	52
Below C	0	0	0	0	0	20	3	23
Total	1	307	258	355	139	68	3	1131

Accuracy ratio=0.8488

Table B11: Out-of-sample Prediction in Elastic net_AIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	1	29	54	0	0	0	0	84
AA	0	111	108	14	1	0	0	234
A	0	2	153	78	13	0	0	246
BBB	0	0	5	171	155	24	0	355
BB	0	0	0	2	60	69	6	137
B	0	0	0	0	1	23	28	52
Below C	0	0	0	0	0	7	16	23
Total	1	142	320	265	230	123	50	1131

Accuracy ratio=0.4730

Table B12: Out-of-sample Prediction in Elastic net_BIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	84	0	0	0	0	0	84
AA	0	212	22	0	0	0	0	234
A	0	12	224	10	0	0	0	246
BBB	0	0	12	340	3	0	0	355
BB	0	0	0	5	132	0	0	137
B	0	0	0	0	4	48	0	52
Below C	0	0	0	0	0	23	0	23
Total	0	308	258	355	139	71	0	1131

Accuracy ratio=0.8453

Table B13: Out-of-sample Prediction in Penalized continuation ratio model_AIC in CDSIRs

	Predicted CDSIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	6	77	1	0	0	0	0	84
AA	0	204	30	0	0	0	0	234
A	0	14	213	19	0	0	0	246
BBB	0	0	11	340	4	0	0	355
BB	0	0	0	5	130	2	0	137
B	0	0	0	0	2	47	3	52
Below C	0	0	0	0	0	15	8	23
Total	6	295	255	364	136	64	11	1131

Accuracy ratio=0.8382

Table B14: Out-of-sample Prediction in Penalized continuation ratio model_BIC in CDSIRs

	Predicted CDIRs							
Actual CDSIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	11	73	0	0	0	0	0	84
AA	0	212	22	0	0	0	0	234
A	0	12	224	10	0	0	0	246
BBB	0	0	12	340	3	0	0	355
BB	0	0	0	5	132	0	0	137
B	0	0	0	0	4	48	0	52
Below C	0	0	0	0	0	23	0	23
Total	11	297	258	355	139	71	0	1131

Accuracy ratio=0.8550

We cross tabulate predicted against observed EQIRs outcomes in contingency Tables B15 to B21 for the in-sample prediction.

Table B15: In-sample Prediction in Ordered probit model in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	1	14	0	0	0	0	0	15
AA	1	409	31	0	0	0	0	441
A	0	17	2491	118	0	0	0	2626
BBB	0	0	75	2902	64	0	0	3041
BB	0	0	0	57	1259	17	0	1333
B	0	0	0	0	14	173	0	187
Below C	0	0	0	0	0	0	0	0
Total	2	440	2597	3077	1337	190	0	7643

Accuracy ratio=0.9466

Table B16: In-sample Prediction in LASSO_AIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	15	0	0	0	0	0	15
AA	0	412	29	0	0	0	0	441
A	0	24	2488	114	0	0	0	2626
BBB	0	0	98	2879	64	0	0	3041
BB	0	0	0	67	1251	15	0	1333
B	0	0	0	0	10	176	1	187
Below C	0	0	0	0	0	0	0	0
Total	0	451	2615	3060	1325	191	1	7643

Accuracy ratio=0.9428

Table B17: In-sample Prediction in LASSO_BIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	15	0	0	0	0	0	15
AA	0	412	29	0	0	0	0	441
A	0	25	2487	114	0	0	0	2626
BBB	0	0	100	2877	64	0	0	3041
BB	0	0	0	68	1249	16	0	1333
B	0	0	0	0	12	175	0	187
Below C	0	0	0	0	0	0	0	0
Total	0	452	2616	3059	1325	191	0	7643

Accuracy ratio=0.9420

Table B18: In-sample Prediction in Elastic net_AIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	15	0	0	0	0	0	15
AA	0	412	29	0	0	0	0	441
A	0	24	2488	114	0	0	0	2626
BBB	0	0	97	2880	64	0	0	3041
BB	0	0	0	67	1251	15	0	1333
B	0	0	0	0	10	175	2	187
Below C	0	0	0	0	0	0	0	0
Total	0	451	2614	3061	1325	190	2	7643

Accuracy ratio=0.9428

Table B19: In-sample Prediction in Elastic net_BIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	15	0	0	0	0	0	15
AA	0	412	29	0	0	0	0	441
A	0	25	2487	114	0	0	0	2626
BBB	0	0	100	2877	64	0	0	3041
BB	0	0	0	68	1249	16	0	1333
B	0	0	0	0	12	175	0	187
Below C	0	0	0	0	0	0	0	0
Total	0	452	2616	3059	1325	191	0	7643

Accuracy ratio=0.9420

Table B20: In-sample Prediction in Penalized continuation ratio model_AIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	15	0	0	0	0	0	15
AA	0	412	29	0	0	0	0	441
A	0	24	2488	114	0	0	0	2626
BBB	0	0	99	2878	64	0	0	3041
BB	0	0	0	67	1249	17	0	1333
B	0	0	0	0	13	174	0	187
Below C	0	0	0	0	0	0	0	0
Total	0	451	2616	3059	1326	191	0	7643

Accuracy ratio=0.9422

Table B21: In-sample Prediction in Penalized continuation ratio model_BIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	15	0	0	0	0	0	15
AA	0	412	29	0	0	0	0	441
A	0	24	2488	114	0	0	0	2626
BBB	0	0	99	2878	64	0	0	3041
BB	0	0	0	68	1249	16	0	1333
B	0	0	0	0	13	174	0	187
Below C	0	0	0	0	0	0	0	0
Total	0	451	2616	3060	1326	190	0	7643

Accuracy ratio=0.9422

We cross tabulate predicted against observed EQIRs outcomes in contingency Tables B22 to B28 for the out-of-sample prediction.

Table B22: Out-of-sample Prediction in Ordered probit model in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	1	0	0	0	0	0	1
AA	9	99	6	0	0	0	0	114
A	2	36	444	17	0	0	0	499
BBB	0	10	65	316	5	0	0	396
BB	0	0	8	45	97	2	0	152
B	0	0	0	0	3	17	0	20
Below C	0	0	0	0	0	0	0	0
Total	11	146	523	378	105	19	0	1182

Accuracy ratio=0.8232

Table B23: Out-of-sample Prediction in LASSO_ AIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	1	0	0	0	0	0	1
AA	0	109	5	0	0	0	0	114
A	0	10	473	16	0	0	0	499
BBB	0	0	41	347	8	0	0	396
BB	0	0	0	27	123	2	0	152
B	0	0	0	0	1	17	2	20
Below C	0	0	0	0	0	0	0	0
Total	0	120	519	390	132	19	2	1182

Accuracy ratio=0.9044

Table B24: Out-of-sample Prediction in LASSO_ BIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	1	0	0	0	0	0	1
AA	0	109	5	0	0	0	0	114
A	0	10	473	16	0	0	0	499
BBB	0	0	41	347	8	0	0	396
BB	0	0	0	27	125	0	0	152
B	0	0	0	0	2	17	1	20
Below C	0	0	0	0	0	0	0	0
Total	0	120	519	390	135	17	1	1182

Accuracy ratio=0.9061

Table B25: Out-of-sample Prediction in Elastic net_AIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	1	0	0	0	0	0	1
AA	0	109	5	0	0	0	0	114
A	0	10	473	16	0	0	0	499
BBB	0	0	41	347	8	0	0	396
BB	0	0	0	27	123	2	0	152
B	0	0	0	0	1	17	2	20
Below C	0	0	0	0	0	0	0	0
Total	0	120	519	390	132	19	2	1182

Accuracy ratio=0.9044

Table B26: Out-of-sample Prediction in Elastic net_BIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	1	0	0	0	0	0	1
AA	0	109	5	0	0	0	0	114
A	0	10	473	16	0	0	0	499
BBB	0	0	41	347	8	0	0	396
BB	0	0	0	27	125	0	0	152
B	0	0	0	0	2	18	0	20
Below C	0	0	0	0	0	0	0	0
Total	0	120	519	390	135	18	0	1182

Accuracy ratio=0.9069

Table B27: Out-of-sample Prediction in Penalized continuation ratio model_AIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	1	0	0	0	0	0	1
AA	0	109	5	0	0	0	0	114
A	0	9	474	16	0	0	0	499
BBB	0	0	41	347	8	0	0	396
BB	0	0	0	27	125	0	0	152
B	0	0	0	0	2	18	0	20
Below C	0	0	0	0	0	0	0	0
Total	0	119	520	390	135	18	0	1182

Accuracy ratio=0.9078

Table B28: Out-of-sample Prediction in Penalized continuation ratio model_BIC in EQIRs

	Predicted EQIRs							
Actual EQIRs	AAA	AA	A	BBB	BB	B	Below C	Total
AAA	0	1	0	0	0	0	0	1
AA	0	109	5	0	0	0	0	114
A	0	9	474	16	0	0	0	499
BBB	0	0	41	347	8	0	0	396
BB	0	0	0	27	125	0	0	152
B	0	0	0	0	2	18	0	20
Below C	0	0	0	0	0	0	0	0
Total	0	119	520	390	135	18	0	1182

Accuracy ratio=0.9078

Appendix C

In this section, we report the relative performance using DM, HLN and MCS tests.

C.1 Main Exercise

The realizations of the DM test for all models under study in the out-of-sample period (2004-2006) are presented in Tables C1 and C2.

Table C1: Diebold Mariano Tests of out-of-sample prediction of CDSIRs

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	22.80***	24.02***	22.62***	23.99***	24.08***	24.01***
Lasso	AIC		~	21.74***	-4.51***	21.59***	21.91***	21.74***
	BIC			~	-21.47***	-2.00**	-2.19**	1.94*
Elastic net	AIC				~	21.33***	21.60***	21.49***
	BIC					~	-1.54	3.33***
Penalized continuation ratio model	AIC						~	3.00***
	BIC							~

Notes: The table reports the DM statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level.

Table C2: Diebold Mariano Tests of out-of-sample prediction of EQIRs

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	9.33***	9.42***	9.33***	9.50***	9.55***	9.55***
Lasso	AIC		~	1.00	~	1.34	1.63	1.63
	BIC			~	-1.00	1.00	1.41	1.41
Elastic net	AIC				~	1.34	1.63	1.63
	BIC					~	1.00	1.00
Penalized continuation ratio model	AIC						~	~
	BIC							~

Notes: The table reports the DM statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level

The HLN statistics are presented in Tables C3 and C4.

Table C3: HLN tests of out-of-sample prediction of CDSIRs

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	22.79***	24.01***	22.61***	23.98***	24.07***	24.00***
Lasso	AIC		~	21.73***	-4.51***	21.58***	21.90***	21.73***
	BIC			~	-21.46***	-2.00**	-2.19**	1.94*
Elastic net	AIC				~	21.32***	21.59***	21.48***
	BIC					~	-1.54	3.33***
Penalized continuation ratio model	AIC						~	3.00***
	BIC							~

Notes: The Table reports the HLN statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level

Table C4: HLN tests of out-of-sample prediction of EQIRs

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	9.33***	9.42***	9.33***	9.50***	9.55***	9.55***
Lasso	AIC		~	1.00	~	1.34	1.63	1.63
	BIC			~	-1.00	1.00	1.41	1.41
Elastic net	AIC				~	1.34	1.63	1.63
	BIC					~	1.00	1.00
Penalized continuation ratio model	AIC						~	~
	BIC							~

Notes: The Table reports the HLN statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level

The MCS p-values are presented in Table C5.

Table C5: MCS tests for out-of-sample prediction

	CDSIRs	EQIRs
Model Name	MSC p-value	MSC p-value
Ordered Probit Model	0.0000	0.0000
LASSO_AIC	0.0000	0.2563*
LASSO_BIC	0.0749*	0.2563*
Elasticnet_AIC	0.0000	0.2563*
Elasticnet_BIC	0.0278	0.2563*
Penalized Continuation Ratio Model_AIC	0.0278	0.2563*
Penalized Continuation Ratio Model_BIC	1.0000*	1.0000*

Note: The Table reposts the MCS p-values. * denotes that the model is belongs to the set of "best" models under the 5% significance level.

C.2 Robustness test: Investment-grade ratings

The realizations of the DM test for all models applied to the task of out-of-sample forecasting the investment ratings are presented in Tables C5 and C6.

Table C6: Diebold Mariano Tests of out-of-sample prediction of CDSIRs (investment-grade ratings)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	12.59***	12.47***	12.59***	12.47***	12.76***	12.71***
Lasso	AIC		~	-2.24**	~	-2.24**	3.90***	3.63***
	BIC			~	-2.24**	~	4.52***	4.28***
Elastic net	AIC				~	-2.24**	3.90***	3.63***
	BIC					~	-4.52***	4.28***
Penalized continuation ratio model	AIC						~	-1.42
	BIC							~

Notes: The table reports the DM statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level.

Table C7: Diebold Mariano Tests of out-of-sample prediction of EQIRs (investment-grade ratings)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	18.84***	18.76***	18.84***	18.76***	18.72***	18.83***
Lasso	AIC		~	-0.58	~	-0.58	-0.63	1.34
	BIC			~	0.58	~	-0.33	2.00**
Elastic net	AIC				~	-0.58	-0.63	1.34
	BIC					~	-0.33	2.00**
Penalized continuation ratio model	AIC						~	2.24**
	BIC							~

Notes: The table reports the DM statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level.

The HLN statistics of all models applied to the task of predicting the investment-grade ratings are presented in Tables C8 and C9.

Table C8: HLN Tests of out-of-sample prediction of CDSIRs (investment-grade ratings)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	12.58***	12.46***	12.58***	12.46***	12.75***	12.70***
Lasso	AIC		~	-2.24**	~	-2.24**	3.90***	3.63***
	BIC			~	-2.24**	~	4.52***	4.28***
Elastic net	AIC				~	-2.24**	3.90***	3.63***
	BIC					~	-4.52***	4.28***
Penalized continuation ratio model	AIC						~	-1.42
	BIC							~

Notes: The Table reports the HLN statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level

Table C9: HLN Tests of out-of-sample prediction of EQIRs (investment-grade ratings)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	18.83***	18.75***	18.83***	18.75***	18.71***	18.82***
Lasso	AIC		~	-0.58	~	-0.58	-0.63	1.34
	BIC			~	0.58	~	-0.33	2.00**
Elastic net	AIC				~	-0.58	-0.63	1.34
	BIC					~	-0.33	2.00**
Penalized continuation ratio model	AIC						~	2.24**
	BIC							~

Notes: The Table reports the HLN statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level

The MCS p-values are reported in Table 10.

Table C10: MCS tests for out-of-sample prediction (investment ratings)

	CDSIRs	EQIRs
Model Name	MSC p-value	MSC p-value
Ordered Probit Model	0.0000	0.0000
LASSO_AIC	0.0110	0.1473*
LASSO_BIC	0.0110	0.1473*
Elasticnet_AIC	0.0110	0.1473*
Elasticnet_BIC	0.0110	0.1473*
Penalized Continuation Ratio Model_AIC	1.0000*	0.1473*
Penalized Continuation Ratio Model_BIC	0.0522*	1.0000*

Note: The Table reposts the MCS p-values. * denotes that the model is belongs to the set of “best” models under the 5% significance level.

C.3 Robustness test: pre-crisis period

The DM statistics of all models in the out-of-sample of the restricted dataset (2006) are presented below.

Table C11: Diebold Mariano Tests of out-of-sample prediction of CDSIRs (2006)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	35.70***	35.84***	35.68***	35.84***	35.45***	35.94***
Lasso	AIC		~	7.13***	1.67*	7.13***	-4.08***	7.28***
	BIC			~	-6.79***	~	-8.83***	-0.47
Elastic net	AIC				~	6.79***	-4.64***	6.93***
	BIC					~	-8.83***	-0.47
Penalized continuation ratio model	AIC						~	9.13***
	BIC							~

Notes: The table reports the DM statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level.

Table C12: Diebold Mariano Tests of out-of-sample prediction of EQIRs (2006)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	34.29***	34.30***	34.29***	34.30***	34.24***	34.25***
Lasso	AIC		~	1.00	~	1.00	-1.41	-1.13
	BIC			~	-1.00	~	-1.89*	-1.63
Elastic net	AIC				~	1.00	-1.41	-1.13
	BIC					~	-1.89*	-1.63
Penalized continuation ratio model	AIC						~	1.00
	BIC							~

Notes: The table reports the DM statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level.

The relevant HLN statistics are in tables C13 and C14.

Table C13: HLN Tests of out-of-sample prediction of CDSIRs (2006)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	35.69***	35.83***	35.67***	35.83***	35.44***	35.93***
Lasso	AIC		~	7.13***	1.67*	7.13***	-4.08***	7.28***
	BIC			~	-6.79***	~	-8.83***	-0.47
Elastic net	AIC				~	6.79***	-4.64***	6.93***
	BIC					~	-8.83***	-0.47
Penalized continuation ratio model	AIC						~	9.13***
	BIC							~

Notes: The Table reports the HLN statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level

Table C14: HLN Tests of out-of-sample prediction of EQIRs (2006)

		Ordered probit model	LASSO		Elastic net		Penalized continuation ratio model	
			AIC	BIC	AIC	BIC	AIC	BIC
Ordered probit model		~	34.28***	34.29***	34.28***	34.29***	34.23***	34.24***
Lasso	AIC		~	1.00	~	1.00	-1.41	-1.13
	BIC			~	-1.00	~	-1.89*	-1.63
Elastic net	AIC				~	1.00	-1.41	-1.13
	BIC					~	-1.89*	-1.63
Penalized continuation ratio model	AIC						~	1.00
	BIC							~

Notes: The Table reports the HLN statistics. *** denotes that the DM null hypothesis of equal predictive accuracy is rejected at the 1% significance level

The MCS p-values of all models in the out-of-sample of the second robustness test are in Table C15.

Table C15: MCS tests for out-of-sample prediction (2006)

	CDSIRs	EQIRs
Model Name	MSC p-value	MSC p-value
Ordered Probit Model	0.0000	0.0000
LASSO_AIC	0.0000	0.2650*
LASSO_BIC	1.0000*	1.0000*
Elasticnet_AIC	0.0000	0.2650*
Elasticnet_BIC	0.6195*	0.2650*
Penalized Continuation Ratio Model_AIC	0.0000	0.2650*
Penalized Continuation Ratio Model_BIC	0.6195*	0.2650*

Note: The Table reposts the MCS p-values. * denotes that the model is belongs to the set of “best” models under the 5% significance level.