Value Investing in Credit Markets

Maria Correia
London Business School
mcorreia@london.edu

Scott Richardson
London Business School
srichardson@london.edu

İrem Tuna
London Business School
ituna@london.edu

May 17, 2011

Abstract

We outline a parsimonious empirical model to assess the relative usefulness of accounting- and equity market-based information to explain corporate credit spreads. The primary determinant of corporate credit spreads is the physical default probability. We compare existing accounting-based and market-based models to forecast default, and find that a modified structural model with accounting and market inputs is best able to forecast default and explain cross-sectional variation in credit spreads. We then assess whether the credit market completely incorporates this default information into credit spreads. Interestingly, we find that credit spreads reflect information about forecasted default rates with a significant lag. This unique evidence is suggestive of a role for value investing in credit markets.

JEL classification: G12; G14; M41
Key words: credit markets, CDS, bonds, default prediction.

* We are grateful to seminar participants at Kepos Capital LP, London Business School, Moody's Analytics, Mark Carhart, Doug Dwyer, Erika Jimenez, Stephen Schaefer, Kari Sigurdsson, Jing Zhang, and Julie Zhang for helpful discussion and comments. We are especially grateful to Moody's/KMV for making available a history of point in time EDF data. Any errors are our own.

1. Introduction

In this paper we outline a framework to forecast corporate credit spreads. Credit markets have become an increasingly common source of finance for publicly traded firms. For example, at the start of the 1980s the total value of U.S. corporate bonds was about $500 billion, and by the end of 2009 this amount had grown to nearly $7 trillion (Securities Industry and Financial Markets Association, 2010). Furthermore, the last two decades has seen a phenomenal growth in secondary trading for many credit-related instruments. The global credit default swap (CDS) market was estimated at about $920 billion in 1998, but by the end of 2009 this had grown to $30.5 trillion (International Swaps and Derivatives Association Inc., 2010).

There has been a keen interest among practitioners and academic researchers for understanding the pricing of credit related instruments. Starting with a simple contingent claims framework (e.g., Merton 1974), the primary determinants of credit spreads are default and loss given default. There is a very long literature in financial economics exploring default prediction models (e.g., Beaver 1966, Altman 1968 and Ohlson 1980). We take this literature as a starting point to evaluate the relative usefulness across accounting and market based information to forecast (out-of-sample) corporate defaults. Prior research has tended to focus on the prediction of corporate defaults without any attempt to link those forecasts back to credit markets.

A primary contribution of our paper is to link models of corporate default to actual credit spreads. A lot of prior academic research has examined the forecast accuracy of default and bankruptcy prediction models, but no paper has linked that forecasting accuracy to actual credit market data. In so doing we are able to triangulate views of default to markets that are supposed to directly incorporate this outcome. To do this we examine the ability of different forecasts of corporate default to explain cross-sectional variation in actual credit spreads. We use each forecast of corporate default combined with a fixed set of model inputs to derive a theoretical (or implied) credit spread. The theoretical (implied) spread based on the 'better' forecasts of default, ceteris paribus, should be able to explain more of the cross-sectional variation in actual credit spreads.

Finally, we examine whether credit markets appear to efficiently incorporate these default forecasts. Akin to the large literature in financial economics which explains the cross-section of equity returns with measures such as book-to-price or intrinsic-value-to-price, we introduce 'value' or unexpected default intensity as a candidate measure to explain the cross-section of credit returns. Our aim is to provide an *anchor* to the evaluation of credit spreads, with that anchor tied to the most important primitive construct for credit spreads: default.

For a sample of 1,767 (194,981) bankrupt (non-bankrupt) firm-year observations over the 1980-2010 period, we find that the best models of default prediction combine market and accounting information. The best default forecast is Expected Default Frequency (EDF) from Moody's/KMV, closely followed by the combined accounting and market model from Beaver, Correia and McNichols (2011), distance to default and Bharath and Shumway (2008). When using these physical default probabilities to explain cross-sectional variation in credit spreads across corporate bond and CDS data, we find a high correlation between the ability of a given default forecasting model to forecast default out-of-sample, and its ability to explain credit spread levels. Again we find that modified structural model approaches to forecasting default (e.g., KMV's EDF) are able to explain up to 42 (50) percent of the cross-sectional variation in corporate bond (CDS) spreads.

Our primary interest in this paper, though, is not to generate the best out-of-sample default or bankruptcy forecast. We are most interested in developing a framework to best utilize a given default or bankruptcy prediction to then forecast credit spread changes. For a sample of nearly 2,000 corporate bonds over the 150 months from January 1997 to June 2009, we find that default forecasts combining market and accounting based information are able to forecast *changes* in credit spreads. Specifically, we find that the difference between default probability implicit in credit spreads and our forecast default probabilities is highly mean reverting, and that this difference is negatively associated with credit spread changes over the next six months. This predictive result is robust to a variety of research design choices including weighted least squares, industry demeaning, returns computed from corporate bonds or CDS contracts, and controlling for known characteristics that explain equity returns (e.g., momentum, size, beta, earnings-to-price, and book-to-price). Thus, similar to equity markets, there is a clear and economically important role for incorporating fundamental value into credit markets.

The rest of the paper is structured as follows. Section 2 lays out a framework for linking forecasts of corporate default to credit spreads and describes our economic hypotheses. Section 3 describes our candidate measures of corporate default probabilities and the credit market data that are used in our empirical tests. Section 4 presents our empirical analysis and section 5 concludes.

2. A framework for forecasting default and credit spreads

2.1 What is a defensible forecast of default?

There exists a number of forecasting models for corporate default. The main types of forecasting models include (i) ad hoc combinations of accounting ratios to discriminate between defaulting and non-defaulting firms (e.g., Beaver 1966, Altman 1968 and Ohlson 1980), (ii) ad hoc combinations of market based information such as equity returns and equity volatility (e.g., Beaver, McNichols and Rhie, 2005 and Bharath and Shumway 2008), and (iii) combinations of these approaches (e.g., Beaver, McNichols and Rhie, 2005).

Instead of developing another ad hoc forecasting model incorporating financial statement based ratios, we lay out a standard contingent claims framework to make the best use of available accounting and market information to forecast default. This approach has been commercialized by Moody's/KMV but it is a very useful framework to evaluate alternative forecasts of default (see e.g., Crosbie and Bohn, 2003).

In the Merton (1974) structural model of credit spreads, the primitive construct is the asset value of the firm and its evolution through time. If we define the asset value of firm *i* at time *t* as $V_{A_{i,t}}$, the corresponding asset volatility as $\sigma^2_{A_{i,t}}$, and the book value of the firm's contractual liabilities due at time *t* as $X_{i,t}$, then we are interested in generating a forecast of the probability that the asset value of the firm is less than the book value of its debt.

More formally we are trying to estimate:

$$PD_{i,t} = \Pr[\ln(V_{A_{i,t}}) \leq \ln(X_{i,t})] \tag{1}$$

We use a standard option-pricing framework to describe the evolution of asset values. The value of assets at time t, $V_{A_{i,t}}$ is then a direct function of original asset values, $V_{A_{i,0}}$, asset volatility, $\sigma^2_{A_{i,t}}$, drift in the underlying asset value, μ_i, the time to default that we are forecasting, *t*, and the Brownian motion shocks to asset values, $\varepsilon_{i,t}$. We can then re-write equation (1) as follows:

$$PD_{i,t} = \Pr[\ln(V_{A_{i,0}}) + (\mu_i - \frac{\sigma_{A_{i,t}}^2}{2})t + \sigma_{A_{i,t}} \sqrt{t}\varepsilon_{i,t} \leq \ln(X_{i,t})] \quad (2)$$

Equation (2) can then be re-arranged to arrive at a more familiar expression as follows:

$$PD_{i,t} = \Pr[-\frac{\ln \frac{V_{A_{i,0}}}{X_{i,t}} + (\mu_i - \frac{\sigma_{A_{i,t}}^2}{2})t}{\sigma_{A_{i,t}} \sqrt{t}} \geq \varepsilon_{i,t}] \quad (3)$$

Equation (3) simply states that the physical probability of default for firm *i* at time *t* is a decreasing function of distance to default. The expression inside the brackets of equation (3) is the ratio of the market value of the assets of the firm relative to the book value of its contractual obligations, $\ln \frac{V_{A_{i,0}}}{X_{i,t}}$, with a modification for drift on asset value, $\mu_i - \frac{\sigma_{A_{i,t}}^2}{2}$, relative to its asset volatility, $\sigma_{A_{i,t}}^2$. The greater the distance between the market values of assets and the book value of debt, *relative* to the underlying asset volatility, the lower the probability of default.

Equation (3) is based on many simplifying assumptions about the capital structure of the firm. Much recent research in finance has sought to extend and improve upon the original Merton (1974) structural model (see e.g., Schaefer and Strebulaev (2008) for a discussion). For example, equation (3) is silent on off-balance sheet obligations, options to refinance and rollover existing contractual obligations, revolving credit lines, convertibility issues etc. We deliberately ignore these complications for our empirical application of equation (3) for the sake of simplicity and discuss some potential implications of this choice in section 4.4.

It is also important to differentiate equation (3) from the typical market model used in existing research. Beaver, Correia and McNichols (2011) describe the standard market model as a linear combination of excess stock returns, market capitalization and equity volatility. Equation (3) is different in several respects. First, the relevant measures are asset-based and not equity-based. Second, it is not changes in equity values (or asset values) that matter, but the relative closeness of the market value of assets to the book value of debt. Third, volatility needs to be considered in a relative manner, not as an additional explanatory variable. It is not asset volatility per se that matters, but the closeness of the market value of assets to the book value of debt for a given level of asset volatility.

One objective of this paper is to assess the out-of-sample predictive ability of empirical applications of equation (3) relative to the existing ad hoc accounting- and market-based models which we describe in more detail in section 3.2. We will use the Expected Default Frequency (EDF) measure of physical default probability from Moody's/KMV, as well as our own crude version of distance to default, $D2D_{i,t}$ for this empirical exercise.

2.2 How can a forecast of default be incorporated into credit spreads?

Once we have a candidate measure of physical default probability, we need to convert the physical probability into a risk-neutral measure to be able to compare it with credit market data, as the pricing in the credit market is risk neutral. It is not sufficient to examine simple linear relations between credit spreads and measures of physical default probability. Credit spreads are a function of more than just physical default probabilities, and more importantly the relation between credit spreads and default probabilities is *not* linear. For example, small changes in default probability at low levels of default probability matter more than for a similar size change in default probability at higher levels of default probability.

Fortunately, there are well-defined and empirically tractable approaches to map forecasts of physical default probability to credit spreads. One such approach is described in Kealhofer (2003b), and Arora, Bohn and Zhu (2005) and we use that approach here. In that setup, credit spreads, $CS_{i,t}$, have five key components: (i) physical default probability, $PD_{i,t}$, (ii) recovery rates given a default, $R_{i,t}$, (iii) risk premia, λ, (iv) correlation of the firm's assets to the market portfolio, $r_{i,t}^2$, and (v) duration or time of exposure to credit risk, *T*.

The probability of default described in section 2.1 is physical, but the pricing in credit market is risk neutral. One key aspect of the conversion of $PD_{i,t}$ into $CS_{i,t}$ is switching from physical probabilities to risk neutral probabilities by incorporating 'risk' into the default probability. Consider firm *i* at time *t* with a simple capital structure consisting of $1 of debt due T years from now. Further, the cumulative *risk-neutral* probability of default over the next T years is $CQDF_{i,t}$, and recovery in the event of default is $R_{i,t}$, i.e., a creditor will receive back 'R cents on the dollar' in the event of default. In this simple model default can only happen T years from now. Thus, there are two possible outcomes T years from now: you receive $1 with probability $1 - CQDF_{i,t}$, or you receive $R with probability $CQDF_{i,t}$. The present value of these *risk-neutral* outcomes today is:

$$PRICE = e^{-rT}[1*(1 - CQDF_{i,t}) + R*CQDF_{i,t}] \qquad (4)$$

The price of the credit instrument can also be written directly as a function of a 'credit spread' as follows:

$$PRICE = e^{-(r+CS_{i,t})T} \qquad (5)$$

By setting equations (4) and (5) equal to each other we can solve for the credit spread, $CS_{i,t}$, as follows:

$$CS_{i,t} = -\frac{1}{T}\ln[1-(1-R_{i,t})CQDF_{i,t}] \tag{6}$$

Equation (6) simply states that a credit spread is an increasing function of *risk-neutral* default probabilities and a decreasing function of recovery rates. However, these are risk-neutral default probabilities. Given that the default probabilities described in section 2.1 are physical (or real-world) default probabilities, we need to convert these physical default probabilities into risk-neutral default probabilities, incorporating some notion of 'risk premium'.

In order to achieve this conversion, we make some empirical choices for tractability. The distance to default reflected in equation (3) is described without reference to any distribution. To convert physical probabilities to risk neutral probabilities we use a normal distribution. This choice does not assume that the default generating process is normally distributed; it allows us to map between physical default probabilities and risk-neutral default probabilities in a simple way. Specifically, we follow the approach described in Kealhofer (2003b) and Arora, Bohn and Zhu (2005) as follows:

$$CQDF_{i,t} = N[N^{-1}[CPD_{i,t}] + \lambda\sqrt{r_{i,t}^2}\sqrt{T}] \tag{7}$$

$CPD_{i,t}$ is the cumulative physical default probability which is computed directly from $PD_{i,t}$ by cumulating survival probabilities over the relevant number of periods. For simplicity we assume a flat term structure for default probabilities, so $CPD_{i,t}$ can be computed directly as $1-(1-PD_{i,t})^T$. The first component of the expression in equation (7) is converting the cumulative physical default probability to a point in the cumulative normal distribution. The second component of equation (7) adds a 'risk' premium to this selected point. Equation (7) assumes that the systematic risk associated with the credit instrument is explained by a single market factor, λ, and a firm specific loading to that factor, $r_{i,t}^2$ (see e.g., Kealhofer, 2003b). Risk is thus the combination of an asset specific risk component (i.e., the correlation between the underlying asset returns and the market index return as measured by $r_{i,t}^2$), and a multiplier that reflects the general level of market risk (i.e., the market Sharpe ratio as measured by λ) as well as the duration of the credit risk exposure (i.e., *T*). Finally, equation (7) then maps this risk modified physical default probability back to the risk neutral space, leaving us with our cumulative risk-neutral default probability.

The above framework links forecasts of default directly to credit spreads. We use this framework to evaluate various models of default to identify the best default forecast to explain both cross-sectional variation in credit spread levels as well as forecast future credit returns. Although there are other components of credit spreads, most notably recovery rates, $R_{i,t}$, and risk premia, λ and $r_{i,t}^2$, we hold them constant across the various default forecasting models that we evaluate, and focus on $PD_{i,t}$. In sub-section 4.4.6 we discuss the sensitivity of our results to alternative choices for these parameters.

2.3 Our empirical hypotheses (tests)

We conduct three sets of empirical analyses. First, we assess the relative (out-of-sample) performance of different forecasts of corporate default. Second, we assess the ability of these default forecasts to explain cross-sectional variation in credit spreads. Third, we assess the ability of these default forecasts to identify relative value (or mispricing) investment opportunities across credit instruments.

2.3.1 Out-of-sample forecast accuracy of default

The common approach in the academic literature to assess default forecasting models is via classification accuracy. We are interested in forecasting default in the next twelve months using data available in month *t*. Therefore, the 'best' default forecasting model will most effectively discriminate between defaulting and non-defaulting firms over the next twelve months. Absent an agreed upon loss function to assess the relative costs of Type I errors (i.e., classifying a firm as a defaulter when it does not default) and Type II errors (i.e., failing to classify a firm as a defaulter and it does default), it is challenging to select across default forecasting models.

We use the 'power curve' or 'receiver operating characteristic' curve to evaluate the various default forecast models for each cross-section. These curves provide summary measures to assess relative forecasting accuracy of binary events. The curves are constructed by sorting each cross-section from most likely to default to least likely default based on a given default forecasting model, and then reporting the frequency of actual defaults along the same continuum. For example, if there are 1000 firms in the cross-section and 10 of these firms default in the next twelve months, then a perfect default forecasting model would identify these 10 firms as having the highest probability of default. The closer a given model gets to ranking these 10 firms as most likely to default, then the better that model. The relevant summary statistic from these power curves is the area beneath the curve, with a value closer to one signalling a better forecast.

We use these power curves to assess the out-of-sample classification accuracy across a set of default forecasting models described in section 3.1. Our priors are that default forecasting models based on first principles within a modified structural model will exhibit better out-of-sample classification accuracy, relative to the existing accounting- and market-based models in the academic literature.

2.3.2 Ability of forecasts of default to explain credit spread levels

We next turn to the ability of a given physical default probability to explain cross-sectional variation in credit spreads. As discussed in section 2.2, we convert the annual physical default probabilities to theoretical (implied) credit spreads. Our priors are that the quality of the default forecast model will also determine its ability to explain cross-sectional variation in credit spreads.

2.3.3 Ability of forecasts of default to forecast changes in credit spreads

We next turn to assessing the information content in the difference between the actual credit spread, $CS_{i,t}$, and the theoretical credit spread, $CS^*_{i,t}$. We denote this difference as credit relative value, $CRV_{i,t}$, and compute it as $\ln\left(\frac{CS_{i,t}}{CS^*_{i,t}}\right)$, or the percentage deviation. An interpretation of $CRV_{i,t}$ is the difference between the implicit physical default probability extracted from credit spreads and the explicit physical default probability modelled from accounting and market information within a contingent claims framework. To the extent that the credit market has not fully incorporated this information, and will do so with a lag, we expect a convergence between the actual credit spread and the theoretical spread implied from the contingent claims framework. Conversely, if the credit market has completely incorporated information about physical default probability then we would not expect to see any convergence between the actual credit spread and the theoretical spread implied from the contingent claims framework. Thus, our primary null hypothesis is as follows:

H1: Actual credit spreads do not converge to theoretical credit spreads implied from a contingent claims framework.

We test H1 using several approaches. First, we employ a time series specification, to test the mean reversion in the difference between actual and theoretical credit spreads. These tests are performed for each bond or CDS contract using the longest possible time series, and results are aggregated across bonds and CDS contracts. Specifically, we define $CRV_{i,t}$ as the difference between the actual and theoretical credit spread for instrument *i* (bond or CDS contract) at time *t*. We compute multiple measures of $CRV_{i,t}$ to correspond to each of the candidate measures of default probability. We then examine whether this difference is mean reverting using the Dickey-Fuller (1979) unit root test. This corresponds to estimating the following regression equation for each bond or CDS contract:

$$CRV_{i,t+K} - CRV_{i,t+K-1} = \alpha_i + \delta_i CRV_{i,t} + \mu_{i,t} \quad (8)$$

where the relevant test is whether $\delta_i = 0$. Finding evidence of $\delta_i < 0$ is consistent with a mean-reverting series.

Second, we conduct standard cross-sectional return predictability regressions. The time series analysis of (8) is only a necessary condition to establish that the actual and theoretical credit spreads converge. We are more interested in establishing the *direction* of that convergence. To empirically evaluate the direction of convergence, we examine whether the difference between actual and theoretical credit spreads is able to forecast future (i) *changes* in actual credit spreads, or (ii) credit returns using the return approximation outlined in Lok and Richardson (2011). For the sake of brevity, we focus on forecasting of credit returns, but note the results are very similar if we instead use changes in credit spreads. To do this, we run the following cross-sectional regression using the Fama and Macbeth (1973) approach:

$$RET_{i,t+K} = \alpha_t + \beta_t CRV_{i,t} + \varepsilon_{i,t} \quad (9)$$

We estimate this regression K times every month, with K reflecting the number of months into the future we are forecasting. To ease with interpretation of the results we examine each month separately (i.e., the returns are not cumulated across K months, but instead focus on the *Kth* month). The relevant test is whether $\beta_t = 0$, and finding $\beta_t > 0$ is consistent with actual credit spreads reverting to the theoretical credit spread.

There are, of course, multiple interpretations if we are able to reject H1, i.e., find $\beta_t > 0$. First, convergence of actual credit spreads to theoretical credit spreads is consistent with a degree of market inefficiency in credit markets, or alternatively a role for forecasting of default (value investing) in credit markets. Second, part of the difference between actual and theoretical credit spreads can be attributed to risk premia. Hence finding an association between this difference and future changes in credit spreads of future credit returns may simply reflect that risk. Third, there could be measurement error in other inputs used in the determination of the credit spread (e.g., recovery rates). In the empirical analysis that follows we will try to differentiate amongst these competing explanations.

Finally, it is also worth noting that the existing literature in financial economics finds that structural models of credit risk tend to understate actual credit spreads (e.g., Huang and Huang 2003 and Schafer and Strebulaev 2008). This will create a positive bias in our $CRV_{i,t}$ measure (i.e., actual credit spreads will tend to be above the theoretical credit spread). This positive bias per se is not a problem for us as the understatement of credit spreads from theoretical models tends to be very persistent and our empirical tests in this section focus on forecasting directional *changes* in actual credit spreads. However, to help mitigate concerns of this bias, we also perform our empirical tests by demeaning our dependent and independent variables at the industry or rating level. To the extent that differences in recovery rates, risk premium, and liquidity vary by industries and rating levels, this approach should mitigate the concern about any bias in CRV explaining our results.

3. Variables and sample selection

3.1 Bankruptcy data and default forecasting models

We estimate the probability of default based on a sample of Chapter 7 and Chapter 11 bankruptcies filed between 1980 and the end of 2010. We combine bankruptcy data from four main sources: Beaver, Correia and McNichols (2011) (BCM)[1], bankruptcy.com, Mergent FISD and Lynn Lo Pucki's bankruptcy database.

Following Shumway (2001), we estimate probabilities of bankruptcy by using a discrete time hazard model and including three types of observations in the estimation: non-bankrupt firms, years before bankruptcy for bankrupt firms and bankruptcy years. Also following Shumway (2001), we exclude financial firms with SIC codes 6021, 6022, 6029 and 6036 and winsorize all independent variables at 1 and 99%. We estimate coefficients using an expanding window approach. We convert the different scores into probabilities as follows: Prob=$e^{score}/1+e^{score}$.

In contrast to earlier studies, we use quarterly financial data and update market data on a monthly basis to obtain monthly estimates of annual probabilities of default.

[1] Beaver, Correia and McNichols (2011) combine the bankruptcy database from Beaver, McNichols and Rhie (2005), which was derived from multiple sources including CRSP, Compustat, Bankruptcy.com, Capital Changes Reporter and a list provided by Shumway with a list of bankruptcy firms provided by Chava and Jarrow and used in Chava and Jarrow (2004).

Market variables are measured at the end of each month and accounting variables are based on the most recent quarterly information reported prior to the end of the month. We ensure that all independent variables are observable prior to the declaration of bankruptcy. We assume that financial statements are available by the end of the second month after the firm's fiscal quarter-end. Our dependent variable is equal to 1 if a firm files for bankruptcy within 1 year of the end of the month. Following prior literature, we keep the first bankruptcy filing and remove from the sample all months subsequent to this filing.

In the next sub-sections, we describe the four default forecast models that we include in our empirical analyses. In unreported analyses we have also examined an additional five default forecast models (Altman, 1968; Ohlson, 1980; accounting model from Beaver, Correia and McNichols, 2011; market model from Beaver, McNichols and Rhie, 2005; credit ratings). For the sake of brevity we have excluded presenting these results as they were inferior relative to the four default forecast models examined below[2]. These results are available upon request.

All of the models are non-linear transformations of various accounting and market data using the discrete time hazard approach described in Shumway (2001). For the sake of brevity, when describing the models below we omit this non-linear transformation, although we implement it.

3.2.1 Distance to Default (D2D) Model

[2] We compare the ability of the default prediction models in correctly predicting bankruptcies based on the area under the Receiver Operating Curves (ROC). Based on this comparison, we find that the areas under the ROC for the models we use in our main analysis are significantly larger. The finding that market-based models we use for our main analysis perform better than pure accounting-based models is consistent with Hillegeist et al. (2004).

To generate a physical default probability consistent with the framework described in section 2.1 we make some simplifying assumptions. First, we ignore time varying complications associated with capital structure such as convertibility, refinancing etc. We compute our default barrier, X_{it}, by combining short-term and long debt consistent with Bharath and Shumway (2008). Specifically, we add short-term debt ('DLCQ') and half of the reported value for long-term debt ('DLTTQ') as reported at the most recent fiscal quarter. We use the book value of debt as it is the book value and not the market value that must be repaid to creditors. We consider only half of the long-term debt. The choice of 50 percent of long-term debt may appear ad hoc, but it is consistent with industry and academic research (e.g., Bharath and Shumway 2008), as long-term debt is less relevant in forecasting default over the next year. Second, we ignore the drift term associated with asset values. Third, we measure asset volatility, $\sigma_{A_{i,t}}$, as the unlevered standard deviation of monthly stock returns from CRSP. This is computed over the previous twelve months, and we use market leverage to 'de-lever' the equity return series. Fourth, we measure the market value of assets as the sum of the market value of equity (computed from CRSP) and the book value of debt. We do not have market values spanning the full set of debt instruments so we are restricted to book values for this calculation.

We then combine the measures described above to generate a default probability from this distance to default as follows:

$$E[PD_{i,t}^{D2D}] = f\left(\frac{\ln\frac{V_{A_{i,0}}}{X_{i,t}}}{\sigma_{A_{i,t}}\sqrt{t}}\right) \quad (10)$$

3.2.2 Beaver, Correia and McNichols (2011) combined model

BCM (2011) generate a combined accounting and market based default forecast model as follows:

$$E[PD_{i,t}^{BCM-BOTH}] = f(NROAI_{i,t}, ROA_{i,t}, \frac{TL}{TA_{it}}, \frac{EBIT}{TL}_{it}, RETURNS_{i,t}, \sigma_{E_{i,t}}, LRSIZE_{i,t}, \\ NROAI_{i,t} * ROA_{i,t}, NROAI_{i,t} * \frac{TL}{TA_{it}}, NROAI_{i,t} * \frac{EBIT}{TL}_{it}, NROAI_{i,t} * \frac{EBIT}{TL}_{it}) \quad (11)$$

$NROAI_{i,t}$ is an indicator variable equal to one if the return on assets, $ROA_{i,t}$, is negative and zero otherwise. It is a measure of profitability difficulties and is positively associated with default. $ROA_{i,t}$ is return on assets defined as the ratio of trailing twelve month earnings before interest (computed as 'NIQ' + 'XINTQ' * (1 – tax_rate, using Compustat mnemonics), where tax_rate is from Nissim and Penman (2001), to average total assets over the corresponding twelve month period. It is a measure of profitability to the asset base of the firm and is negatively associated with default. $\frac{TL}{TA_{it}}$ is total liabilities ('LTQ') divided by total assets '(ATQ') measured as at the end of the most recent fiscal quarter. It is a measure of leverage (credit risk) and is positively associated with default. $\frac{EBIT}{TL}_{it}$ is the ratio of trailing twelve month operating income before depreciation ('OIBDPQ') to average total liabilities ('LCTQ') for the corresponding twelve month period. This is a measure of current profitability and is negatively associated with default.

$RETURNS_{i,t}$ is the prior twelve month equity returns as extracted from the CRSP monthly files. This is a measure of changes in market value and is negatively associated with default. $\sigma_{E_{i,t}}$ is the standard deviation of excess stock returns computed over the previous twelve months. Monthly stock returns are extracted from CRSP and a one factor CAPM is used to compute excess returns. This is a measure of equity volatility and is positively associated with default. $LRSIZE_{i,t}$ is the logarithm of the ratio of market capitalization of firm *i* for month *t* relative to the market capitalization of all firms for month *t*. The market capitalization is computed from the CRSP monthly files as '|PRC|' * SHROUT. $LRSIZE_{i,t}$ is a measure of relative firm size and is negatively associated with default.

Finally, BCM (2011) include a full set of interactions for their accounting variables to allow the relation between accounting variables and default to differ for profit making firms relative to loss making firms.

3.2.3 Bharath and Shumway (2008)

BS (2008) generate a combined accounting- and market-based default forecast model as follows:

$$E[PD_{i,t}^{BS}] = f(\frac{NI}{TA_{it}}, RETURNS_{i,t}, \frac{1}{\sigma_{E_{i,t}}}, X_{i,t}, SIZE_{i,t}, \pi_{D2Dit}) \qquad (12)$$

$\frac{NI}{TA_{it}}$ is the ratio of trailing twelve month net income ('NIQ') to average total assets for the corresponding twelve month period. This is a measure of current profitability and is negatively associated with default. $RETURNS_{i,t}$ and $\sigma_{E_{i,t}}$ are as defined in section 3.2.2. X_{it} is the sum of short-term debt ('DLCQ') and half of long-term debt ('DLTTQ') consistent with previous academic and industry research as discussed in section 3.2.1. It is a measure of contractual liabilities and is positively associated with default. $SIZE_{it}$ is the logarithm of market capitalization based on the CRSP monthly files at the start of that month ('|PRC|' * SHROUT). It is a measure of firm size and is negatively associated with default. π_{D2Dit} is a naïve default probability calculated based on distance to default as $N(-D2D_{it})$.

3.2.4 Moody's/KMV EDF Model

The Expected Default Frequency (EDF) score provided by Moody's/KMV is a 'black box' from our perspective. However, Crosbie and Bohn (2003) explain the procedure use by Moody's/KMV to arrive at a physical default probability. Essentially, they initially estimate asset value and asset volatility to compute the distance to default as described in section 2.1. They combine information from equity markets and financial statements very similar to our $D2D_{i,t}$ measure described in section 3.2.1. This measure of distance to default is then empirically mapped to a large set of corporate default data that they have access to from a consortium of banks. There are multiple sources of additional richness in EDF relative to our estimated $D2D_{i,t}$, including (i) explicit incorporation of industry level asset volatility, (ii) superior set of default data, and (iii) incorporation of additional convexity in the relation between D2D and physical default probability by not limiting the empirical mapping to a logistic transformation.

3.3 Credit market data

We collect data for credit markets from two sources. First, we collect the monthly Merrill Lynch corporate bond index data. These files contain a complete set of data for investment grade and high yield corporate bonds in North America. We extract bond identification information to map the respective issue back to the relevant issuer to ensure correct identification of financial statement and equity market data. We further select corporate bonds that have duration as close to five years as possible. We choose five years as corporate bonds tend to be more liquid at this range and also to allow for comparability with credit spreads from the CDS market where the liquidity is greatest also for the five-year CDS contracts. We also impose a hard cut-off that effective duration must be between three to eight years. When there are multiple bonds for a given issuer that fall within this duration classification we then select the bond which has the largest market value to help ensure we are selecting the most liquid corporate bond. Our final bond sample covers more than 2000 corporate bonds over the 1997 to 2010 period.

Second, we collect CDS data from DataStream. We collect 5-year credit default swap (CDS) spreads from January 2005 to April 2010 limiting our analysis to senior, USD denominated CDS contracts with modified restructuring clauses. Our final CDS sample covers 484 issuers over the 2005 to 2010 period.

We compute returns for corporate bonds and CDS contracts as per the approach outlined in Lok and Richardson (2011). Specifically, an approximate measure of *monthly* credit returns from the perspective of the seller of protection, using 5-year CDS data is as follows:

$$RET_{i,t\rightarrow t+1}^{CREDIT} = \frac{1}{12} CS_{i,t} - Duration_{i,t} * \Delta CS_{i,t\rightarrow t+1} \qquad (13)$$

$RET_{i,t\rightarrow t+1}^{CREDIT}$ is the credit return for the month for firm i from the start to the end of the month. $CS_{i,t}$ is the credit spread for firm i on day t. $Duration_{i,t}$ is the spread duration for the credit contract for firm i on day t. $\Delta CS_{i,t\rightarrow t+K}$ is the change in credit spread for firm i for the month. For our corporate bond sample we use credit spreads and duration measures as reported from Merrill Lynch. We also have access to total returns as well as an abnormal bond return (after subtracting the return from a duration-matched Treasury instrument). The correlation between our imputed return and the total return is above 0.95, so not surprisingly our results are similar across both of these measures of credit returns. For our CDS sample we use CDS spreads as reported from DataStream.

4. Results

4.1 Predicting defaults

Our expanding window estimation of the various default forecasting models described in section 3.2 generates regression coefficients that are consistent with our priors. We do not report the regression estimates for the sake of brevity but they are available upon request. To help visualize the various physical default probabilities generated across the four default forecasting models, we have plotted the mean, 25^{th}, 50^{th} and 75^{th} percentiles of the various default forecasting models in Figure 1. We plot these cross-sectional values for each of the 367 months for which we have data over the January 1980 to July 2010 period (the time series for EDF is only from January 1997 to 2010). Across all four models, it is clear that default probabilities exhibit temporal variation as expected: the distributions shift to the right in economic downturns.

Table 1 reports the correlations across the four physical default probabilities. For each month we compute the pair-wise correlations across each of the default probabilities described in section 3.2. We do not require non-missing data for every model each month. Instead we use the greatest number of observations to compute each correlation. We then report averages of these pair-wise correlations across the 367 months from January 1980 to July 2010. There is a robust positive association across all of the default forecasting models. The average Pearson (Spearman) correlation is 0.586 (0.665) for our full sample (not reported in table).

Figure 2 contains the "Receiver Operating Characteristics" curves for the different models. A model with no predictive power for bankruptcy would have a ROC curve along the 45-degree line. The further away the ROC curve is from that line, the higher the model's predictive power. These curves are directly comparable as they are generated from a fixed sample of firm-years where there is sufficient data to estimate each of the four default forecasts. To assess statistical significance of the difference across the default prediction models, we compute pair-wise differences between the Area Under the Curve ("AUC") each month and use 367 month time series to conduct statistical tests correcting for the eleven month over-lapping period using a Newey-West (1987) correction. We see that $PD_{i,t}^{EDF}$ dominates the other three models in terms of ex post classification accuracy, albeit the differences across the models are relatively small in economic magnitude and not statistically significant.

In unreported analysis, we also compute an implied default probability from actual credit spreads using equations (6) and (7). We find that this implied default probability is statistically inferior to $PD_{i,t}^{EDF}$.

4.2 Explaining cross-sectional variation in credit spreads

We now turn to actual credit market data to assess the relative ability of the various default forecasting models to explain cross-sectional variation in actual credit spreads, $CS_{i,t}$. This analysis is limited to the period January 1997 to July 2010 as we require bond data from Merrill Lynch. For each firm, we select the largest bond outstanding that has a duration between 3 to 8 years. This is to help ensure cross-sectional comparability across bond spreads. We use the option-adjusted spreads as reported by Merrill Lynch to evaluate the theoretical spreads from each of the default forecasting models.

We compute theoretical spreads across the default forecasting models as described in section 2.2. We first convert the one year ahead physical default probability for model *j* to a five year cumulative physical default probability as follows: $CPD_{i,t}^{j} = 1-(1-PD_{i,t}^{j})^{5}$. We then assume that the recovery rate is 40 percent (common industry practice), use the average value of the market Sharpe Ratio of 0.5 and assume the average asset correlation is 40 percent. These choices are by necessity arbitrary but are supported by industry practice and choices from previous research (see e.g., Kealhofer 2003a, 2003b, and Arora, Bohn and Zhang 2005). In section 4.4.6 we assess the sensitivity of our results to alternative choices for these parameters. We then compute a theoretical spread for the *jth* model as per equation (6).

Table 2 compares the sample of firms for which we have corporate bond market data with the full sample. In Panel A we report data for the full sample of firm-months used in default prediction. In Panel B we report data for the full sample for the post-1997 period as this is where our credit market data starts. In Panel C we report the firm-months in the post-1997 period, for which we have non-missing corporate bond data. Comparing values across Panels B and C, we find that firms with non-missing corporate bond data have a higher ROA on average than the other firms in our full sample (0.0428 vs. -0.0408), are less likely to report losses (12.97% vs. 33.15%), have higher leverage ratios (0.6997 vs. 0.5034), lower volatility in returns (0.0933 vs 0.1296), a higher $\frac{EBIT}{TL}_{it}$ ratio (0.1980 vs. 0.0060) and a lower book-to-market ratio (0.5362 vs.0.6128).

Panel D compares the industry composition of the two samples. There is a higher percentage of manufacturing firms and lower percentage of finance firms in the bond sample. Business equipment firms represent a lower proportion of the bond sample.

Table 3 reports the average pair-wise correlations across the default forecasting models for the reduced sample of firms where we have available bond market data, and enables us to compare these correlations with those discussed earlier for the full cross-section of firms. The correlation structure across the physical default probabilities is quite similar for this reduced sample. Specifically, the average of the difference between the Pearson (Spearman) pair-wise correlations between Table 1 and Table 3 is -0.029 (0.016) respectively. Relative to the average correlations of about 0.5 in both tables, these differences are small.

Panel A of Table 4 reports the cross-sectional details for the various theoretical spreads. Across all theoretical spreads, we see clear evidence that the actual market spread is greater than that from the models. In the second column for each model, we report the frequency of cases where the actual spread is greater than the theoretical spreads. Consistent with prior research (e.g., Schaefer and Strebulaev 2008), we see that theoretical spreads are lower than actual spreads in more than 70 percent of cases across all measures.

Panel B of Table 4 reports the correlations between the actual credit spread, $CS_{i,t}$, and, $CS_{i,t}^{j}$, the theoretical spread for the *jth* model. The average pair-wise Pearson (Spearman) correlation across the four theoretical credit spread measures and $CS_{i,t}$ is 0.611 (0.588) respectively. The model with the highest (lowest) correlations with credit spreads is $CS_{i,t}^{EDF}$. Perhaps it is not too surprising to see that forecasts of default from intermediaries whose business is to forecast default are best able to explain cross-sectional variation in spread levels.

One approach to consider the consistency across default prediction per se and explaining cross-sectional credit spreads is to look at the correlation in the relevant summary statistics across both approaches. For out-of-sample default prediction the relevant summary statistic was the area under the curve. For explaining cross-sectional variation in credit spreads the relevant statistic is the pair-wise correlation between the model spread and the actual spread using a constant sample size. Using a constant sample size to ensure comparability across all of the default measures, we find that the Pearson (Spearman) correlation across these summary statistics is 0.637 (0.800) respectively.

4.3 Predicting future credit returns (or changes in credit spreads)

Having established the relative ability of forecasts of physical default probability to (i) accurately classify bankruptcy out-of-sample, and (ii) explain credit spread levels, we now turn to the more ambitious task of assessing whether the difference between the physical default probability implicit in actual credit spreads and our forecasts of physical default probability has any information content. As described in section 2.3.3 we evaluate the information content of this default probability difference using two sets of tests.

Table 5 reports the distribution of bond specific regressions of mean reversion in the difference between actual spreads, $CS_{i,t}$, and theoretical spreads, $CS_{i,t}^{j}$, across our *j* models. We estimate equation (8) for each bond in our sample requiring each bond to have at least 12 months of data. Our final sample for these time series regressions is between 1,777 and 2,196 bonds across the four default forecasting models for one month ahead, and 1,419 and 1,727 for six months ahead.

Table 5 reports the mean reversion in the difference between actual spreads, $CS_{i,t}$, and theoretical spreads, $CS_{i,t}^{j}$ for the next *six* months. This allows us to also consider the relative speed in mean reversion. We report the average as well as 10th, 25th, 50th, 75th, and 90th percentiles for the respective δ_i coefficient (see also Collin-Dufresne, Goldstein and Martin 2001). Across all of our default forecast models, there is very strong evidence of mean reversion in the difference between actual and theoretical credit spreads. For example, the mean δ_i for one (six) month(s) ahead across the four reported default forecasting models range between -0.2125 and -0.1692 (-0.0650 and -0.0432). In the final row of each panel we also report the *cumulative* mean reversion over the next six months. Across the four default forecast models, we see that about 67 percent of the difference between actual and theoretical spreads mean reverts over the next six months. This relation is quite robust as evidenced by negative coefficients for the 90th percentile of the sample. Across the set of bond specific regressions we find that the average explanatory power of these regressions is between 6 and 8 (30 and 35) percent for the next one (six) month(s). We also find very strong evidence of statistical significance across the bond specific regressions, with a range of 21 to 28 (71 to 80) percent of bonds having statistically significant mean reversion over the next one (six) month(s). The statistical tests for the cumulative mean reversion are based on Newey-West (1987) standard errors with correction for five over-lapping periods. What these tests do not tell us, however, is whether actual credit spreads move toward theoretical spreads or vice versa.

We now turn to direct tests of how the difference between actual and theoretical credit spreads leads changes in actual credit spreads. If our forecasts of default are 'good' and the market does not fully incorporate this information into credit spreads then the difference should be able to forecast changes in credit spreads.

As described in section 2.3.3, we regress future credit returns on the current difference between actual and theoretical spreads. Our priors are for a positive regression coefficient because actual credit spreads are expected to revert to the theoretical credit spread (and credit returns are inversely related to changes in credit spreads).

Table 6 reports the regression results for an expanded version of equation (9). In addition to our $CRV_{i,t}$ measures we also include characteristics that have previously been shown to explain the cross-section of equity returns. Inclusion of these variables should help account for potential risk based explanations. Specifically, we estimate the following regression:

$$\begin{aligned} RET_{i,t+k} &= \alpha_t + \beta_{CRV} CRV_{i,t} + \beta_{UMD} UMD_{i,t} + \beta_{UMD2} UMD2_{i,t} + \beta_{BTM} BTM_{i,t} \\ &+ \beta_{SIZE} SIZE_{i,t} + \beta_{E/P} E/P_{i,t} + \beta_{BETA} BETA_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (14)$$

$UMD_{i,t}$ is the equity return for issuer i for the most recent month (i.e., the month prior to the start of the credit return cumulation period). $UMD2_{i,t}$ is an exponentially weighted cumulative return over the eleven months prior to the computation of $UMD_{i,t}$. We use an exponential weighting instead of equal weighting because we are interested in capturing the delayed response of credit markets to *recent* information in equity markets. $BTM_{i,t}$ is book-to-price computed as the ratio of book value of equity (Compustat mnemonic 'CEQ') from the recent fiscal quarter relative to market capitalization corresponding to that fiscal period end date. $SIZE_{i,t}$ is the log of market capitalization as at the start of the credit return cumulation period. $E/P_{i,t}$ is the earnings-to-price ratio calculated as the ratio of net income ('NIQ') from the recent four fiscal quarters relative to market capitalization corresponding to that fiscal period end date. $BETA_{i,t}$ is the equity market beta estimated from a rolling regression of 60 months of data requiring at least 36 months of non-missing return data. To the extent that credit and equity markets are linked, we expect to see a positive relation between credit returns and $UMD2_{i,t}$, $E/P_{i,t}$, $BETA_{i,t}$, and $BTM_{i,t}$, and a negative relation between credit returns and $SIZE_{i,t}$. Unlike equity markets, however, we do not expect to see the short-term reversal effect (e.g., Jegadeesh, 1990). This is attributable to micro-structure issues that are specific to the market in which a given instrument is traded. We expect a positive relation between credit returns and $UMD_{i,t}$ due to slower price discovery in corporate bond markets relative to equity markets.

The inclusion of equity returns is also important to help discriminate across the candidate $CRV_{i,t}$ measures. Some of the default forecasts incorporate equity returns directly (e.g., $PD_{i,t}^{BS}$), and it is important to isolate a pure lagged relation between credit returns and equity returns.

We estimate equation (14) each month (149 months from January 1997 to May 2009) and report averages of regression coefficients (e.g., Fama and Macbeth 1973). We estimate equation (14) using weighted least squares with the weights computed as $-\ln(CS_{i,t})$. This weighting scheme is most consistent with the returns experienced by a risk-aware investor. Ben Dor et al. (2007) show that volatility in credit returns is directly proportional to the product of duration and credit spread level. Given that our cross-sectional estimation is focused on bonds with duration as close to 5 years as possible, the primary driver of cross-sectional differences in credit return volatility for our sample is credit spread level. Our choice of $-\ln(CS_{i,t})$ as the weighting scheme will naturally place less weight on riskier firms for a given credit spread. In unreported results, we find very similar results using equal weighting (results available upon request).

In Table 6 we see that all four of the best default forecasts are able to explain changes in credit spreads over the next one to three months, with the cross-sectional explanatory power of between 6.95 and 7.96 percent for one month ahead, and 5.02 and 5.38 percent for three months ahead. The Fama-Macbeth test statistics of the respective $CRV_{i,t}$ measures range between 4.69 and 9.1 (1.37 and 4.63) for the next one (three) months. It is also important to note the very strong lagged relation between credit returns and recent equity returns (for the one month ahead regression Fama-Macbeth test statistics for β_{UMD} ranges between 7.27 and 8.89). To the extent that the included explanatory variables adequately reflect risk for these credit instruments, the positive relation between future credit returns and the $CRV_{i,t}$ measures is not solely attributable to risk, and suggests some mispricing of physical default probabilities in credit markets. Across all of the regression specifications the best default forecasting models to explain future changes in credit spreads are those that incorporate accounting and market information within a modified structural framework (e.g., $PD_{i,t}^{EDF}$) rather than the more ad hoc combinations (e.g., $PD_{i,t}^{BS}$).

To help provide some evidence on the economic significance of these results, we report portfolio level returns in Table 7. To construct these portfolio returns we first sort each cross section into five equal sized groups based on $CRV_{i,t}^{D2D}$, $CRV_{i,t}^{BCM-BOTH}$, $CRV_{i,t}^{BS}$, and $CRV_{i,t}^{EDF}$. We then compute the average credit return for the next six months (risk weighted) across each of the 149 months. We also report a hedge return as the difference in the average portfolio return across the extreme quintiles. Test statistics are reported based on the time series variation in this hedge return. This approach assumes monthly rebalancing and ignores the impact of any transaction costs. Across the four measures there is strong evidence of an economically significant predictive association between the $CRV_{i,t}$ measures and future credit returns. For example, the Fama-Macbeth test statistic of 8.60 for the $CRV_{i,t}^{BS}$ measure for the next month's credit returns is equivalent to a Sharpe Ratio of 2.44 (see Lewellen 2010 for a mapping of Fama-Macbeth test-statistics to Sharpe Ratios). Across all four measures, the Sharpe Ratio ranges from 0.94 to 2.44 for the first month, declining to 0.25 to 1.20 by the third month. We interpret this as strong evidence against H1.

Our final set of empirical analysis examines the ability of candidate risk factors to explain time series variation in the ex post returns to the respective long/short $CRV_{i,t}$ portfolio returns reported in table 7. This exercise is somewhat exploratory as there is not an agreed upon set of risk factors yet to explain the cross section of *credit* returns. We rely on previous equity asset pricing research and combine a set of changes in macro-economic state variables (see Chen, Roll and Ross, 1986) and standard factor-mimicking portfolio returns (see Fama and French, 1992 and 1993). Using the time series of 149 monthly risk weighted long/short $CRV_{i,t}$ portfolio returns we estimate the following regression:

$$R^{CRV}{}_t = \alpha + \beta^{dRP} dRP_t + \beta^{dTS} dTS_t + \beta^{dVIX} dVIX_t + \beta^{dVIX} dVIX_t + \beta^{dIP} dIP_t + \beta^{MKT} R^{MKT}{}_t + \beta^{SMB} SMB_t + \beta^{HML} HML_t + \beta^{MOM} MOM_t + \varepsilon_t \quad (15)$$

SMB, HML and MOM are the factor-mimicking portfolio returns from Ken French's website. MKT is the excess return to the market portfolio. dRP is the change in corporate risk premium, measured as the change in the default spread (the difference between the Moody's Seasoned BAA Corporate Bond Yield and the 10 year Treasury constant maturity rate). dTS is the change in term structure, measured as the change in the difference between the 10 year Treasury constant maturity rate and the 2 year Treasury constant maturity rate. dVIX is the monthly change in volatility using the average daily valued of the CBOE Volatility Index each month. dIP is the percentage change in Industrial Production for the month.

To the extent that factor-mimicking portfolio returns and the changes in our selected macro-economic state variables reflect compensation for changes in risk profile, we want to control for time series variation in risk in our analysis. Table 8 presents the results for the risk-weighted portfolios (inferences are very similar for the equal weighted portfolios and are not reported for the sake of brevity). There are several important observations to be made. First, across the four default measures we see very significant intercepts which translate into economically and statistically significant conditional Sharpe Ratios (see second to last row in table 8). These large conditional Sharpe ratios suggest that the portfolio returns documented in table 7 cannot be explained by the set of eight risk factors. Of course, it is always possible there is an unidentified risk factor which time varies with our long/short portfolio returns. Second, the included risk factors are able to explain a large proportion of the time series variation in our long/short portfolio returns (with the exception of $CRV_{i,t}^{BS}$). The majority of this explanatory power is attributable to changes in the corporate risk premium (positive) and aggregate equity market returns and changes in industrial production (both negative). These strong associations are explained by the construction of our respective $CRV_{i,t}$ measures. $CRV_{i,t}$ is computed as $\ln\left(\frac{CS_{i,t}}{CS_{i,t}^{*}}\right)$. Thus, there is the potential for a correlation with credit spread level to enter into a given $CRV_{i,t}$ measure. This is particularly true for $CRV_{i,t}^{D2D}$ and $CRV_{i,t}^{EDF}$. These two measures exhibit relatively strong *negative* correlations with credit spread levels. This negative correlation means that the credit return forecast has a bias toward issuers with lower levels of credit spreads. In times of crisis, as reflected by large drops in equity market returns and industrial production and substantial increases in BAA Corporate Bond Yields relative to long-term risk free rates, such a bias in the portfolio will benefit from 'flight to quality' as higher quality credit instruments are bid up. In section 4.4.7 we talk about the impact of removing this spread bias on our reported results.

4.4 Extensions, limitations and robustness analyses

4.4.1 Credit Default Swap (CDS) contracts

Our empirical analysis has so far used option-adjusted spreads from corporate bonds. We chose to focus on bond data as it provides a much longer time series to improve the power of our statistical tests. However, a limitation with the corporate bond data is the lack of cross-sectional comparability in credit spreads due to issue-specific concerns such as duration, optionality and liquidity in the corporate bond market. While we have used option adjusted spreads, restricted our analysis to bonds with a modified duration between 3 and 8 years, and focused only on those corporate bonds that are included in the Merrill Lynch bond indices, there is still a residual concern that credit spreads extracted from corporate bond data is sufficiently noisy to make clean inferences difficult.

As an alternative to corporate bond data, we have re-estimated all of our empirical analysis from sections 4.2 and 4.3 using credit spreads from the CDS market. Rather than tabulate these results we discuss them in the text for the sake of brevity. For our sample of 25,050 firm-months with available 5-year CDS spreads, we find results that are largely similar to those presented in Tables 3 to 8. Across all default forecast models, the implied spread continues to under-forecast actual credit spreads (about 80 percent of spreads are understated on average across default forecasting models). We continue to find significant mean reversion in the difference between actual credit spreads and implied credit spreads. For example, the average value of δ from equation (8) for one (cumulative six) months ahead ranges between -0.0835 and -0.1648 (-0.5363 and -0.6649) respectively, all significantly different from zero at conventional levels. For the estimation of equation (14) for the CDS sample, we continue to find a significant association between lagged equity returns and future credit returns, and a robust relation between $CRV_{i,t}^{D2D}$ and $CRV_{i,t}^{EDF}$ and future credit returns extending out past three months.

4.4.2 Corporate bond returns

Our tabulated results in Tables 6 to 8 are based on an approximation for credit returns computed from credit spread data. We have chosen to report results using this measure as it allows for easier comparability between bond and CDS data. However, it is possible that the analytics used to extract an option-adjusted spread from corporate bond data leads to spurious measures of returns. While we do not believe that this is the case, as the correlation between our imputed credit return based on option adjusted spreads from Merrill Lynch and the total returns reported by Merrill Lynch are above 0.95, we still use the bond returns reported by Merrill Lynch to ensure our results are robust. An advantage of using total bond returns is that you can then subtract off the return from a duration matched risk free instrument to remove cross-sectional variation in interest rate sensitivities across corporate bonds. Our results are unchanged (i.e., all four of the best default forecasts are able to explain changes in credit spreads over the next one to six months). These results are available upon request.

4.4.3 Industry effects

In unreported tests, we also industry demean future credit returns and the $CRV_{i,t}$ measures. We do this to remove any industry-related effects that could be driving our results. The inferences from tables 6 to 8 are, if anything, stronger. We find this result comforting as a lot of our choices in converting a physical default probability to a theoretical credit spread used simplistic cross-sectional constants for recovery rates and asset correlations.

4.4.4 Broader definition of defaults

Our empirical analysis is based on sets of accounting and market based information to predict a set of bankruptcy events for the period 1980 to 2009. The relevant theoretical event is a 'default'. While all bankruptcies are by definition defaults, it is possible to create a broader set of default events encompassing non-bankruptcy related defaults. This is precisely what vendors such as Moody's/KMV are able to do best. They have access to rich default data directly from banks. Unfortunately, we do not yet have access to a large set of default data. We have, however, manually identified a set of default events from the annual reports on corporate default and recovery rates prepared by Moody's. This set of default events is not perfect because in some years we do not have access to relevant date of the default we only know the year of default. We have presented our empirical results based on bankruptcy calibration as we believe this is a cleaner data set. We have re-estimated all of our analysis using the Moody's default dataset. We find very similar results to that reported in the paper (these tables are available upon request).

4.4.5 Transaction costs

The empirical results described in section 4.3 are *suggestive* of market inefficiency in credit markets. We are cautious in making this inference for multiple reasons. First, as described above there are potential rational risk based explanations for this relation (although we have shown that the predictive results are robust to an extensive set of candidate risk measures). Second, the magnitude of the returns may well be within the bounds of transaction costs. Unfortunately, to the best of our knowledge, there is no large sample evidence describing the magnitudes of transaction costs (direct or indirect) for corporate bond or CDS markets. It is almost surely the case that the transaction costs in this market are larger than that for equity markets but the exact level is not clear. As such we caution interpretation of the relation with future credit returns or changes in credit spreads as evidence of an anomalous relation in credit markets.

4.4.6 Alternative parameter choices for equation (7)

All of our reported empirical analysis using equation (7) has used constant values for the market price of risk, λ, firm sensitivity to market risk, $r_{i,t}^2$, and recovery rates, $R_{i,t}$. Our primary focus is on the relative ability of default forecasting models to explain credit spreads and predict changes in credit spreads, so we believe that fixing other parameters of equation (7) facilitates that relative comparison. In this section we discuss alternative parameter values for these constructs and summarize their effect on our reported results.

We have varied the market price of risk from 0.3 to 0.6 which correspond to the values observed in Kealhofer (2003b). Given that λ is essentially a level adjustment in the computation of the implied credit spread, it is not surprising to see that changes in the market price of risk do not affect any of our inferences in Tables 6 through 8.

Instead of using a constant firm specific sensitivity to market risk, we have estimated the correlation between monthly firm stock returns and monthly market returns using a rolling 60 month window. We have imposed a floor (ceiling) on the estimated correlation at 0.1 (0.7) and re-compute the implied credit spreads allowing for this temporal and cross-sectional variation in firm specific sensitivity to market risk. We continue to see (i) an under-forecasting of credit spreads across the default forecasting models (the average under forecasting is 78 percent), (ii) strong mean reversion in the difference between actual and implied credit spreads (δ_i coefficients range between -0.1602 and -0.2094 and between -0.6282 and -0.7426 for the next one and cumulative six months respectively), (iii) strongly significant association between theset of $CRV_{i,t}$ measures and future credit returns (regression coefficients across the four $CRV_{i,t}$ measures from equation (14) continue to have average Fama-Macbeth test statistics between 3.17 and 7.46 and between 0.65 and 3.94 for the next one and three months respectively), and (iv) strong economic significance of the relation between the set of $CRV_{i,t}$ measures and future credit returns (the average Sharpe Ratio for risk weighted portfolios across the four $CRV_{i,t}$ measures is 1.31 and 0.60 and for the next one and three months respectively).

We have not generated firm specific estimates of recovery rates. Instead, we note that the primary determinants of recovery rates are the seniority of the credit instrument and industry membership (Kealhofer, 2003a). For our sample of corporate bonds it is possible that we have differences in seniority that will contaminate cross-sectional comparisons of our measure of implied credit spreads. However, for the sample of CDS contracts described in section 4.4.1 we use only CDS contracts with senior unsecured reference obligations, and we continue to find similar results. Our industry adjusted analysis reported in section 4.4.3 will also help capture cross-sectional differences in recovery rates. But we do recognize the potential for further enhancements to value investing in credit markets by explicitly modelling recovery rates.

4.4.7 Is the return predictability just "carry"?

As discussed at the end of section 4.3, several of the $CRV_{i,t}$ measures examined are correlated with credit spread levels. A potential criticism of the relation between a given $CRV_{i,t}$ measure and future credit returns is that it is merely reflecting "carry", whereby the returns are attributable to exposure to (or away from) risky credit instruments over a time period when the investor does not observe a negative outcome for such risky exposures. While we do not feel this is a valid criticism as the sample period covers at least two economic downturns during the period 1997 to 2010, we have conducted additional analysis to address this issue. Specifically, each month we regress each $CRV_{i,t}$ measure on credit spread levels and use the residual from these regressions in the analysis for Tables 6 to 8. If anything, we find slightly stronger evidence of return predictability with this correction.

4.4.8 Cross-sectional partitions

We have also replicated our empirical analysis on a subset of firms that also have an issuer level credit rating from S&P. This will naturally create a sample of larger and more liquid firms. For this sample, we assess whether the return predictability reported in Tables 6 to 8 varies across investment grade and high yield companies. We find evidence that the return predictability exists for both investment grade and high yield companies, and in some cases the relation is stronger for high yield companies.

4.4.9 Extensions

Our empirical implementation of equation (3) could be extended in many ways. We outline some of these extensions in this sub-section. First, the measure of asset volatility contained within the EDF measure from Moody's/KMV, as well as our own measure of distance to default (D2D) is backward-looking. In recent years, the liquidity and breadth of equity option markets has increased, whereby the implied volatility of put and call contracts could be used to generate more forward looking measures of asset volatility. While there might be issues with matching the duration of the option contract (most equity option contracts are for the next 3 to 6 months and most credit derivatives are for several years), there is the potential for further enhancements from incorporating truly forward-looking information on asset volatility.

Second, actual market prices of credit instruments could be incorporated to improve the measure of asset value. Both EDF and D2D use the sum of market capitalization and the book value of debt to arrive at the market value of assets. The market value of credit can be estimated directly from credit markets. Incorporating such market values should improve the forecasting ability of default forecasts.

Third, the default barrier is very simplistic in both the EDF and D2D measures. Richness in the capital structure, roll-over financing, revolving lines of credit, off-balance sheet obligations etc. are all important real world considerations. Future research could also consider extending D2D measure of default along these lines.

Fourth, there is scope for incorporating industry and economy wide information into the respective default forecast models. While the superior default forecast models all incorporate equity market information, which to some extent reflects the aggregate belief of equity market participants as to the relevance of industry and market wide information, they do not explicitly incorporate industry- and economy-wide forecasts. The EDF measure from Moody's/KMV is an exception which makes use of industry level asset volatility data. Future research could consider explicit macro level forecasts as well to improve default forecasts at the firm level.

5. Conclusion

In this paper we outline an approach to make use of accounting and market based information to forecast corporate default. We evaluate a wide set of default forecasting models that make varying use of accounting and market based information. We find that modified structural model approaches of the type used by Moody's/KMV are best able to forecast bankruptcies out-of-sample for a set of 1,797 bankruptcies over the 1980 to 2010 period. We then find that these superior default forecasts are also able to explain relatively more of the cross-sectional variation in credit spreads for a sample of around 2,000 (453) corporate bonds (CDS contracts_ over the 1997 to 2010 (2005 to 2010) period.

The most interesting result that we document, however, is the predictive information content of these default forecasts relative to the physical default forecast implicit in actual credit spreads. We find a robust positive association between the difference in actual credit spreads and implied credit spreads based on our best default forecast models and future credit returns. This relation is robust to (i) industry controls, (ii) inclusion of known equity risk factors, and (iii) alternative weighting schemes. This positive relation is suggestive of a role for structured use of accounting and equity market based information to serve as an anchor for evaluating actual credit market data.

Future research on recovery rate modelling and improving on the measure of distance to default (e.g., incorporating information on off-balance sheet obligations, modelling drift in asset values directly, making use of actual market values for outstanding debt, etc.) could help improve forecasts of physical default probabilities. This attention to measurement detail should generate better forecasts that can in turn be used as improved anchors to evaluate credit spreads.

References

ALTMAN, E. (1968). “Financial ratios, discriminant analysis and the prediction of corporate bankruptcy.” *Journal of Finance* 23: 589-609.

ARORA, N., J. BOHN and F. ZHU (2005). “Reduced form vs. structural models of credit risk: a case study of 3 models.” Journal of Investment Management 3 (4): 43-67.

BEAVER, W. H. (1966). “Financial ratios as predictors of failure.” *Journal of Accounting Research* 4: 71-102.

BEAVER, W. H., M. MCNICHOLS, and J. RHIE (2005). “Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy.” *Review of Accounting Studies* 10: 93-122.

BEAVER, W.H., M. CORREIA and M. MCNICHOLS (2011). “Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy.” Working Paper.

BEN DOR, A., L. DYNKIN, J. HYMAN, P. HOUWELING, E. Van LEEUWEN, and O. PENNIGA. (2007). “DTS (Duration times Spread).” The Journal of Portfolio Managements, Winter: 77-100.

BHARATH, S. and T. SHUMWAY (2008). “Forecasting default with the Merton distance to default model.” *Review of Financial Studies* 21:1339-1369.

CHAVA, S., and R. JARROW (2004). “Bankruptcy prediction with industry effects.” *Review of Finance* 8: 537-569.

CHEN, N., R. ROLL, and S. A. ROSS (1986). “Economic forces and the stock market.” *The Journal of Business* 59 (1986): 383-403.

COLLIN-DUFRESNE, P., R.S. GOLDSTEIN, and J.S. MARTIN (2001). “The determinants of credit spread changes.” *Journal of Finance*, 56 (6): 2177-2207.

CROSBIE, P. and J. BOHN (2003). “Modelling default risk.” Moody’s KMV.

DICKEY, D.A. and W.A. FULLER (1979). “Distribution of the Estimators for Autoregressive Time Series with a Unit Root.” *Journal of the American Statistical Association* 74: 427–431.

FAMA, E., and K. FRENCH (1992). “The cross-section of expected stock returns.” *Journal of Finance* 47: 427-465.

FAMA, E., and K. FRENCH (1993). “Common risk factors in the returns of stocks and bonds.” *Journal of Financial Economics* 33: 3-56.

FAMA, E. and J. MACBETH (1973). “Risk, Return and Equilibrium: Empirical Tests.” *Journal of Political Economy*, 81 (3): 607-636.

HILLEGEIST, S., E. KEATING, D. CRAM, and K. LUNDSTEDT (2004). "Assessing the probability of bankruptcy." *Review of Accounting Studies* 9 (2004): 1573-7136.

HUANG, J.-Z. and M. HUANG (2003). "How much of the corporate treasury yield spread is due to credit risk?" Working paper University of Pennsylvania.

ISDA (2010) " ISDA Market Survey." International Swaps and derivatives association, Inc..

JEGADEESH, N., (1990). "Evidence of predictable behavior of security returns." *Journal of Finance* 45: 881-898.

KEALHOFER, S.(2003a). "Quantifying Credit Risk I: Default Prediction." *Financial Analysts Journal*, Jan/Feb: 30-44.

KEALHOFER, S.(2003b). "Quantifying Credit Risk II: Debt Valuation." *Financial Analysts Journal*, May/June: 78-92.

LEWELLEN, J. (2010). "Accounting anomalies and fundamental analysis: An alternative view." *Journal of Accounting and Economics*, 50, 455-466.

LOK, S. AND S. RICHARDSON (2011). "Credit markets and financial information." Forthcoming *Review of Accounting Studies.*

MERTON, R. (1974) "On the pricing of corporate debt: The risk structure of interest rates." *Journal of Finance* 29: 449-470.

NEWEY, W. K. and K.D.WEST (1987). "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix." *Econometrica* 55 (3): 703–708.

OHLSON, J. (1980). "Financial ratios and the probabilistic prediction of bankruptcy." *Journal of Accounting Research* 18: 109-131.

SCHAEFER, S. and I. STREBULAEV (2008). "Structural models of credit risk are useful: evidence from hedge ratios on corporate bonds." *Journal of Financial Economics*: 1-19.

SHUMWAY, T. (2001). "Forecasting bankruptcy more accurately: A simple hazard model." *Journal of Business* 74: 101-124.

Securities Industry and Financial Markets Association (2010). "Outstanding U.S. Bond Market Debt Spreadsheet". http://www.sifma.org/research/statistics.aspx

Appendix: Variable definitions

Compustat mnemonics in parenthesis

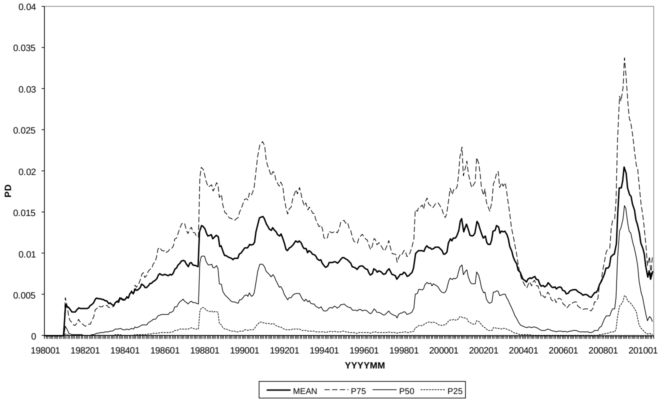
Variable	Description
$BETA_{i,t}$	Equity market beta estimated from a rolling regression of 60 months of data requiring at least 36 months of non-missing return data
$BTM_{i,t}$	Book to market ratio measured at the most recent fiscal quarter end ('CEQQ'/'PRRC'*'CSHOQ')
$CRV_{i,t}$	Credit relative value and is computed as $\ln\left(\frac{CS_{i,t}}{CS^*_{i,t}}\right)$, where $CS^*_{i,t}$ is the theoretical (implied) credit spread for firm i in month t using *D2D, BCM-BOTH, BS,* or *EDF* default prediction model.
$CS_{i,t}$	Actual credit spread for firm i in month t
$CS^{D2D}_{i,t}$	Theoretical (implied) credit spread for firm i in month t using *D2D* default prediction
$CS^{BCM-BOTH}_{i,t}$	Theoretical (implied) credit spread for firm i in month t using *BCM-BOTH* default prediction model
$CS^{BS}_{i,t}$	Theoretical (implied) credit spread for firm i in month t using *BS* default prediction model
$CS^{EDF}_{i,t}$	Theoretical (implied) credit spread for firm i in month t using *EDF* default prediction model
dIP_t	$\ln\left(\frac{IP_t}{IP_{t-1}}\right)$, where IP_t is Industrial Production Index at the end of month t from the Board of Governors of the Federal Reserve System (INDPRO), available at the St Louis Fed web site: http://research.stlouisfed.org/fred2/
dRP_t	Change in risk premium, $RP_t - RP_{t-1}$, where RP_t is the difference between the Moody's Seasoned BAA Corporate Bond Yield from the Board of Governors of the Federal Reserve System (BAA) and the 10-Year Treasury constant maturity rate from the Board of Governors of the Federal Reserve System (GS10). BAA and GS10 are available at the St Louis Fed web site: http://research.stlouisfed.org/fred2/.

Variable	Description
dTS_t	Change in term structure, TS_t- TS_{t-1}, where TS_t is the difference between the 10-Year Treasury constant maturity rate (GS10) and the 2-Year Treasury constant maturity rate (GS2), both from the Board of Governors of the Federal Reserve System. Both GS10 and GS2 are available at the Louis Fed web site: http://research.stlouisfed.org/fred2/
$dVIX_t$	Change in volatility, VIX_t -VIX_{t-1}, where VIX_t is average daily CBOE Volatility Index from the Chicago Board Options Exchange (VIX) for month t. VIX is available at the St Louis Fed web site: http://research.stlouisfed.org/fred2/
$\frac{E}{P}_{it}$	Net Income ('NIQ') from the most recent four quarters divided by the market capitalization at the fiscal period end date.
$\frac{EBIT}{TL}_{it}$	Net income before interest, taxes, depreciation, depletion and amortization ('OIBDPQ') divided by total liabilities ('LT')
HML	Monthly mimicking factor portfolio return to the value factor, obtained from Ken French's website.
$LRSIZE_{i,t}$	Logarithm of the ratio of the firm's market capitalization at the end of the month and the market capitalization of all firms.
MOM	Average return on the two high prior return portfolios minus the average return on the two low prior return portfolios, obtained from Ken French's website.
$\frac{NI}{TA}_{it}$	Net income ('NIQ') divided by average total assets ('ATQ')
$NROAI_{i,t}$	Indicator variable equal to 1 if the return on assets ($ROA_{i,t}$) is negative
$PD_{i,t}^{D2D}$	Physical default probability for firm i in month t using *D2D* default prediction model
$PD_{i,t}^{BCM-BOTH}$	Physical default probability for firm i in month t using *BCM-BOTH* default prediction model
$PD_{i,t}^{BS}$	Physical default probability for firm i in month t using *BS* default prediction model
$PD_{i,t}^{EDF}$	Physical default probability for firm i in month t using *EDF* default prediction model
R^{MKT}	Monthly excess (to risk free rate) market return, obtained from Ken French's website.
$ROA_{i,t}$	Return on assets, defined as earnings before interest ('NIQ') adjusted for interest income tax ('XINTQ'*(1-tax rate)), scaled by average total assets ('ATQ')

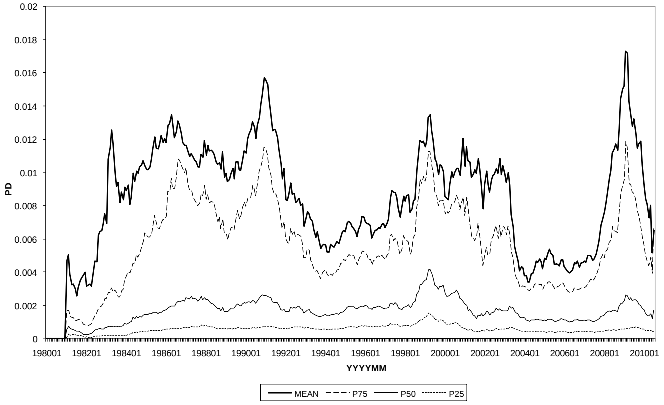
Variable	Description
$RETURNS_{i,t}$	Prior 12 month security returns from CRSP monthly files
$\sigma_{E_{i,t}}$	Standard deviation of excess returns computed over the previous 12 months. Monthly returns are extracted from CRSP and a one factor CAPM is used to compute excess returns
$SIZE_{it}$	Logarithm of market capitalization, calculated at the end of the month as 'PRC'*'SHROUT' from CRSP monthly file.
SMB	Monthly mimicking factor portfolio return to the size factor, obtained from Ken French's website.
$\frac{TL}{TA}_{it}$	Ratio between total liabilities ('LTQ') and total assets ('ATQ')
UMD_{it}	Stock return for month t
$UMD2_{it}$	Three month half life weighted average of stock return for the 11 months ending in the beginning of month t.
$V_{A_{i,t}}$	Market value of equity at the end of the month plus book value of debt (X_{it}), calculated as described below
X_{it}	Book value of short-term debt ('DLCC')+0.5* book value of long-term debt ('DLTTQ')

Figure 1 - Cross-sectional distribution of physical default probabilities

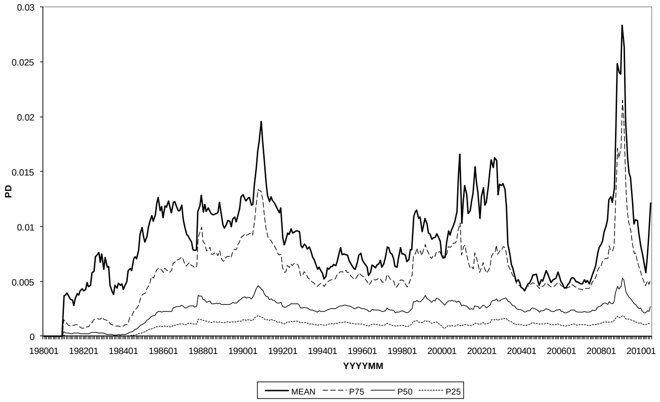
Panel A: $PD_{i,t}^{D2D}$



Panel B: $PD_{i,t}^{BCM-BOTH}$



Panel C: $PD_{i,t}^{BS}$



Panel D: $PD_{i,t}^{EDF}$

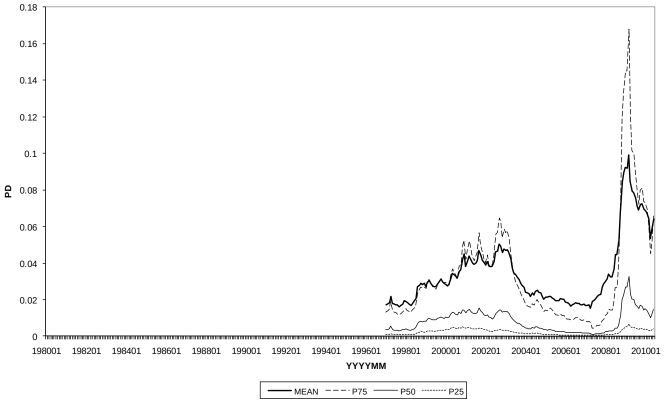
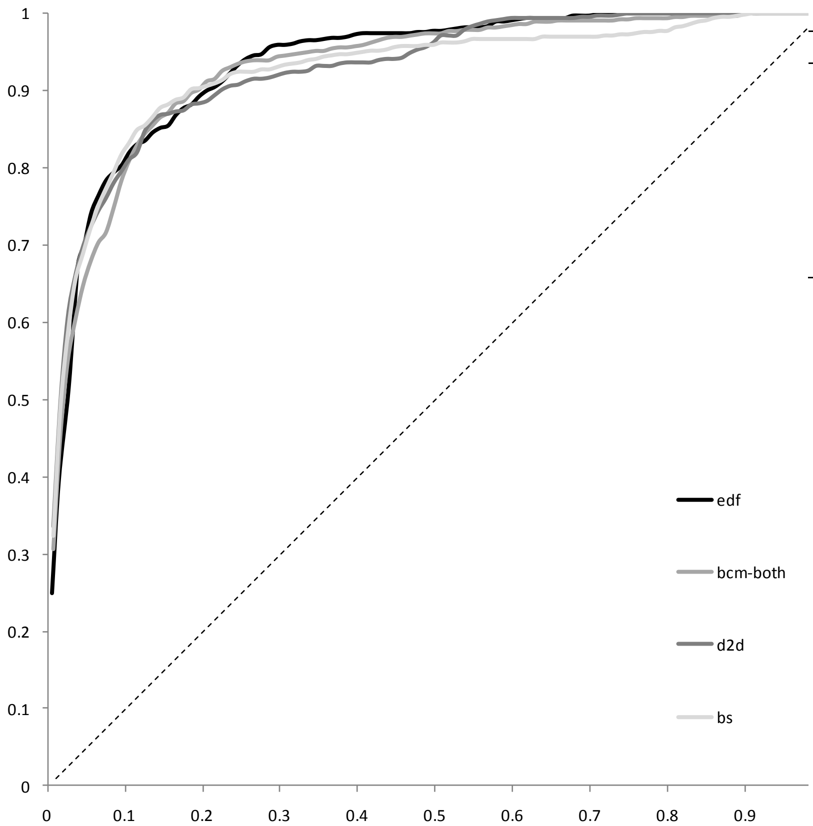


Figure 2

Power Curves for alternative models of physical default probabilities

Constant sample across all models



Model	AUC
$PD_{i,t}^{EDF}$	0.9325
$PD_{i,t}^{BCM-BOTH}$	0.9262
$PD_{i,t}^{D2D}$	0.9244
$PD_{i,t}^{BS}$	0.9216

Table 1

Correlations across physical probability of default (Pearson above diagonal, Spearman below)

	$PD_{i,t}^{D2D}$	$PD_{i,t}^{BCM-BOTH}$	$PD_{i,t}^{BS}$	$PD_{i,t}^{EDF}$
$PD_{i,t}^{D2D}$	1	0.465	0.550	0.674
$PD_{i,t}^{BCM-BOTH}$	0.648	1	0.675	0.580
$PD_{i,t}^{BS}$	0.799	0.709	1	0.571
$PD_{i,t}^{EDF}$	0.701	0.654	0.480	1

Correlations are computed for each of the 367 months for which we have data. Correlations are based on the largest possible sample size for each pair of default forecasts. Reported correlations are averages across the 367 months. Variable definitions are provided in the appendix.

Table 2

Descriptive statistics for the bond and full default sample

Panel A: Descriptives for full sample

	# Firm Months	Mean	25th Percentile	Median	75th Percentile
$NROAI_{i,t}$	1701602	0.2899			
$ROA_{i,t}$	1701602	-0.0170	-0.0201	0.0416	0.0849
$\frac{TL}{TA}_{it}$	1824654	0.5132	0.3065	0.5114	0.6919
$\sigma_{E_{i,t}}$	2061737	0.1237	0.0620	0.0998	0.1574
$\frac{EBIT}{TL}_{it}$	1364698	0.0768	0.0265	0.1854	0.3891
$UMD_{i,t}$	2049456	0.0114	-0.0658	0.0000	0.0693
$UMD2_{i,t}$	2062158	-0.0006	-0.0263	0.0041	0.0289
$BTM_{i,t}$	1769293	0.7443	0.3021	0.5531	0.9049

Panel B: Descriptives for full sample (post 1997)

	# Firm Months	Mean	25th Percentile	Median	75th Percentile
$NROAI_{i,t}$	808075	0.3315			
$ROA_{i,t}$	808075	-0.0408	-0.0491	0.0285	0.0778
$\frac{TL}{TA}_{it}$	845851	0.5034	0.2776	0.4871	0.7007
$\sigma_{E_{i,t}}$	985594	0.1296	0.0613	0.1041	0.1685
$\frac{EBIT}{TL}_{it}$	683057	0.0060	0.0177	0.1609	0.3797
$UMD_{i,t}$	979887	0.0108	-0.0698	0.0016	0.0699
$UMD2_{i,t}$	985767	-0.0035	-0.0293	0.0033	0.0280
$BTM_{i,t}$	821174	0.6128	0.2731	0.5016	0.8224

Panel C: Descriptives for bond sample

	# Firm Months	Mean	25th Percentile	Median	75th Percentile
$NROAI_{i,t}$	91975	0.1297			
$ROA_{i,t}$	91975	0.0428	0.0182	0.0485	0.0768
$\frac{TL}{TA}_{it}$	93982	0.6997	0.5776	0.6876	0.8170
$\sigma_{E_{i,t}}$	95439	0.0933	0.0513	0.0755	0.1151
$\frac{EBIT}{TL}_{it}$	78310	0.1980	0.1081	0.1766	0.2675
$UMD_{i,t}$	95403	0.0071	-0.0557	0.0072	0.0666
$UMD2_{i,t}$	95439	-0.0019	-0.0209	0.0055	0.0262
$BTM_{i,t}$	91508	0.5362	0.2895	0.4736	0.7104

Panel D: Industry composition across full sample and bond only sample

	Full Sample	Full Sample (Post 1997)	Bond Sample
	%	%	%
Consumer Non Durables	5.24	4.42	6.66
Consumer Durables	2.41	2.04	2.45
Manufacturing	10.38	8.39	12.71
Oil, Gas, and Coal Extraction and Products	4.24	3.45	7.51
Chemicals and Allied Products	2.04	1.77	3.82
Business Equipment	16.44	17.4	4.9
Telephone and Television Transmission	2.46	3.23	8.42
Utilities	2.77	2.34	8.91
Wholesale, Retail, and Some Services	8.93	7.81	8.63
Healthcare, Medical Equipment, and Drugs	8.55	9.44	4.23
Finance	23.76	27.92	19.66
Other	12.78	11.77	12.1

Variable definitions are provided in the appendix.

Table 3

Correlations across physical probability of default for reduced sample with bond market data

(Pearson above diagonal, Spearman below)

	$PD_{i,t}^{D2D}$	$PD_{i,t}^{BCM-BOTH}$	$PD_{i,t}^{BS}$	$PD_{i,t}^{EDF}$
$PD_{i,t}^{D2D}$	1	0.464	0.675	0.560
$PD_{i,t}^{BCM-BOTH}$	0.606	1	0.684	0.634
$PD_{i,t}^{BS}$	0.796	0.746	1	0.672
$PD_{i,t}^{EDF}$	0.653	0.547	0.545	1

Correlations are computed for each of the 150 months for which we have data (January 1997 to June 2009). Correlations are based on the largest possible sample size for each pair of default forecasts. Reported correlations are averages across the 150 months. Variable definitions are provided in the appendix.

Table 4

Relation between actual credit (bond) spreads and theoretical credit spreads derived from default forecasting models

Panel A: Descriptive statistics

	N	% Under Forecasted	Average	Std. Dev.	10^{th} percentile	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile
$CS_{i,t}$	95,299		0.0342	0.0438	0.0073	0.0103	0.0187	0.0414	0.0730
$CS_{i,t}^{D2D}$	93,863	0.85	0.0148	0.0182	0.0002	0.0013	0.0071	0.0221	0.0432
$CS_{i,t}^{BCM-BOTH}$	78,279	0.76	0.0128	0.0236	0.0016	0.0026	0.0047	0.0107	0.0313
$CS_{i,t}^{BS}$	90,483	0.78	0.0142	0.0198	0.0038	0.0057	0.0088	0.0140	0.0265
$CS_{i,t}^{EDF}$	76,357	0.71	0.0197	0.0329	0.0012	0.0027	0.0073	0.0197	0.0514

Panel B: Correlations (Pearson above diagonal, Spearman below)

	$CS_{i,t}$	$CS_{i,t}^{D2D}$	$CS_{i,t}^{BCM-BOTH}$	$CS_{i,t}^{BS}$	$CS_{i,t}^{EDF}$
$CS_{i,t}$	1	0.394	0.557	0.545	0.651
$CS_{i,t}^{D2D}$	0.473	1	0.526	0.750	0.599
$CS_{i,t}^{BCM-BOTH}$	0.420	0.608	1	0.734	0.672
$CS_{i,t}^{BS}$	0.417	0.794	0.751	1	0.684
$CS_{i,t}^{EDF}$	0.638	0.653	0.568	0.560	1

Correlations are computed for each of the 150 months for which we have data (January 1997 to June 2009). Correlations are based on the largest possible sample size for each pair of default forecasts. Reported correlations are averages across the 150 months. Variable definitions are provided in the appendix.

Table 5

Mean reversion in the difference between actual and theoretical credit spreads (time series regressions)

$$CRV_{i,t+K} - CRV_{i,t+K-1} = \alpha_i + \delta_i CRV_{i,t} + \mu_{i,t} \qquad \textbf{(8)}$$

Panel A: $CRV_{i,t}^{D2D}$

	# Bonds	*Mean*	*Stddev*	*10^{th} percentile*	*25^{th} percentile*	*50^{th} percentile*	*75^{th} percentile*	*90^{th} percentile*	*Adj R2*	*Pct significant*
t+1	2196	-0.1692	0.1837	-0.4084	-0.2509	-0.1210	-0.0453	0.0024	0.06	21
t+2	2077	-0.1235	0.1460	-0.3048	-0.1918	-0.0977	-0.0361	0.0149	0.04	15
t+3	1981	-0.1018	0.1435	-0.2657	-0.1650	-0.0873	-0.0274	0.0284	0.03	13
t+4	1892	-0.0843	0.1373	-0.2332	-0.1477	-0.0795	-0.0168	0.0436	0.02	13
t+5	1813	-0.0733	0.1332	-0.2095	-0.1355	-0.0723	-0.0146	0.0531	0.01	11
t+6	1727	-0.0568	0.1460	-0.1931	-0.1231	-0.0602	-0.0019	0.0801	0.01	12
Total	1750	-0.6456	0.5117	-1.3008	-0.9692	-0.6099	-0.2966	-0.0552	0.32	73

Panel B: $CRV_{i,t}^{BCM-BOTH}$

	# Bonds	*Mean*	*Stddev*	*10^{th} percentile*	*25^{th} percentile*	*50^{th} percentile*	*75^{th} percentile*	*90^{th} percentile*	*Adj R2*	*Pct significant*
t+1	1865	-0.2102	0.2022	-0.4602	-0.2840	-0.1595	-0.0859	-0.0311	0.08	28
t+2	1747	-0.1523	0.1512	-0.3482	-0.2290	-0.1268	-0.0632	-0.0071	0.05	17
t+3	1656	-0.1231	0.1521	-0.3066	-0.2010	-0.1075	-0.0441	0.0283	0.03	14
t+4	1550	-0.1007	0.1453	-0.2618	-0.1710	-0.0979	-0.0370	0.0510	0.02	12
t+5	1481	-0.0877	0.1549	-0.2481	-0.1524	-0.0892	-0.0241	0.0700	0.02	12
t+6	1402	-0.0650	0.1619	-0.2219	-0.1367	-0.0711	-0.0038	0.0905	0.01	10
Total	1419	-0.7440	0.5229	-1.3442	-1.0314	-0.7140	-0.4225	-0.1746	0.35	80

Panel C: $CRV_{i,t}^{BS}$

	# Bonds	*Mean*	*Std dev*	*10^th^ percentile*	*25^th^ percentile*	*50^th^ percentile*	*75^th^ percentile*	*90^th^ percentile*	*Adj R2*	*Pct significant*
t+1	2129	-0.2125	0.2017	-0.4802	-0.2968	-0.1568	-0.0770	-0.0257	0.08	26
t+2	2005	-0.1432	0.1501	-0.3335	-0.2163	-0.1131	-0.0517	0.0006	0.04	13
t+3	1912	-0.1088	0.1479	-0.2839	-0.1751	-0.0953	-0.0390	0.0203	0.02	11
t+4	1817	-0.0851	0.1343	-0.2334	-0.1503	-0.0825	-0.0257	0.0524	0.01	9
t+5	1740	-0.0722	0.1512	-0.2210	-0.1425	-0.0740	-0.0124	0.0711	0.01	7
t+6	1655	-0.0517	0.1611	-0.2158	-0.1260	-0.0614	0.0048	0.1103	0.01	7
Total	1676	-0.6584	0.4784	-1.2662	-0.9696	-0.6354	-0.3376	-0.1086	0.32	77

Panel D: $CRV_{i,t}^{EDF}$

	# Bonds	*Mean*	*Std dev*	*10^th^ percentile*	*25^th^ percentile*	*50^th^ percentile*	*75^th^ percentile*	*90^th^ percentile*	*AdjR2*	*Pct significant*
t+1	1777	-0.2028	0.2181	-0.4669	-0.2926	-0.1427	-0.0574	-0.0097	0.07	28
t+2	1683	-0.1206	0.1803	-0.3191	-0.1934	-0.0982	-0.0347	0.0146	0.03	13
t+3	1612	-0.0964	0.1794	-0.2581	-0.1542	-0.0800	-0.0191	0.0412	0.02	9
t+4	1545	-0.0634	0.1786	-0.2174	-0.1342	-0.0631	-0.0063	0.0757	0.01	7
t+5	1492	-0.0687	0.2342	-0.2309	-0.1364	-0.0647	-0.0027	0.0804	0.01	6
t+6	1419	-0.0432	0.1949	-0.2131	-0.1166	-0.0475	0.0159	0.1134	0.00	5
Total	1442	-0.6397	0.6464	-1.3131	-0.9602	-0.6181	-0.2821	-0.0437	0.30	71

Equation (8) is estimated for each bond requiring at least twelve months of data. Panels A-D report descriptive statistics for δ_i for K=1 to 6, the adjusted R^2 of these regressions and the percentage of δ_i significant at the 5% level. The last line of each panel, labelled "Total", contains descriptive statistics for the cumulative six months δ_i estimated using the following equation: $CRV_{i,t+6} - CRV_{i,t} = \alpha_i + \delta_i CRV_{i,t} + \mu_{i,t}$. The percentage of significant aggregate δ_i is calculated based on Newey-West adjusted standard errors with five lags. Variable definitions are provided in the appendix.

Table 6

Predictive Regressions [-ln($CS_{i,t}$) weighted] including Fama-French equity characteristics

Cross sectional regressions

$$RET_{i,t+k} = \alpha_t + \beta_{CRV} CRV_{i,t} + \beta_{UMD} UMD_{i,t} + \beta_{UMD2} UMD2_{i,t} + \beta_{BTM} BTM_{i,t} + \beta_{SIZE} SIZE_{i,t} + \beta_{E/P} E/P_{i,t} + \beta_{BETA} BETA_{i,t} + \varepsilon_{i,t} \quad \textbf{(14)}$$

Panel A: $CRV_{i,t}^{D2D}$

	# Months	*Average # Bonds*	α	β_{CRV}	β_{UMD}	β_{UMD2}	β_{BTM}	β_{SIZE}	$\beta_{E/P}$	β_{BETA}	**Adjusted R2**
t+1	149	459	0.0027	0.0012	0.0179	0.0326	0.0011	-0.0009	-0.0022	0.0017	0.0695
			(0.76)	(5.9)	(8.89)	(4.64)	(1.77)	(-2.55)	(-1.19)	(2.94)	
t+2	148	438	-0.0050	0.0011	0.0074	0.0316	0.0003	0.0002	-0.0006	0.0006	0.0555
			(-1.45)	(5.71)	(3.43)	(4.53)	(0.51)	(0.60)	(-0.28)	(1.04)	
t+3	147	422	-0.0011	0.0003	0.0045	0.0174	0.0002	0.0000	-0.0002	-0.0006	0.0502
			(-0.33)	(1.57)	(2.15)	(2.58)	(0.30)	(0.03)	(-0.08)	(-1.03)	
t+4	146	407	-0.0021	0.0006	0.0034	0.0097	-0.0012	0.0000	0.0016	0.0001	0.0487
			(-0.6)	(4.02)	(1.47)	(1.32)	(-1.73)	(0.02)	(0.78)	(0.16)	
t+5	145	393	-0.0030	0.0004	0.0029	0.0172	0.0019	0.0001	0.0000	-0.0010	0.0470
			(-0.85)	(2.11)	(1.34)	(2.45)	(2.39)	(0.41)	(0.00)	(-1.50)	
t+6	144	380	-0.0024	0.0004	0.0015	0.0081	0.0012	0.0001	-0.0008	-0.0008	0.0443
			(-0.69)	(2.68)	(0.6)	(1.15)	(1.39)	(0.31)	(-0.37)	(-1.27)	

Panel B: $CRV_{i,t}^{BCM-BOTH}$

	# Months	*Average # Bonds*	α	β_{CRV}	β_{UMD}	β_{UMD2}	β_{BTM}	β_{SIZE}	$\beta_{E/P}$	β_{BETA}	**Adjusted R2**
t+1	149	393	0.0027	0.0013	0.0164	0.0206	0.0008	-0.0009	-0.0031	0.0009	0.0726
			(0.75)	(4.69)	(8.48)	(2.63)	(1.15)	(-2.49)	(-1.51)	(1.6)	
t+2	148	375	-0.0053	0.0011	0.0063	0.0225	-0.0003	0.0003	-0.0038	-0.0003	0.0562
			(-1.66)	(3.81)	(2.8)	(2.81)	(-0.49)	(0.97)	(-1.66)	(-0.44)	
t+3	147	361	-0.0038	0.0016	0.0022	0.0001	0.0001	0.0001	-0.0008	-0.0011	0.0525
			(-1.22)	(5.49)	(1.01)	(0.01)	(0.19)	(0.4)	(-0.3)	(-1.93)	
t+4	146	348	-0.0032	0.0012	0.0016	-0.0021	-0.0016	0.0001	-0.0012	-0.0002	0.0508
			(-0.99)	(4.2)	(0.59)	(-0.26)	(-2.12)	(0.32)	(-0.54)	(-0.36)	
t+5	145	336	-0.0032	0.0006	0.0016	0.0094	0.0016	0.0001	0.0000	-0.0012	0.0469
			(-0.97)	(2.17)	(0.67)	(1.27)	(1.93)	(0.48)	(0.00)	(-1.98)	
t+6	144	325	-0.0029	0.0005	0.0005	0.0000	0.0009	0.0002	-0.0033	-0.0010	0.0442
			(-0.87)	(1.81)	(0.20)	(0.00)	(1.02)	(0.62)	(-1.37)	(-1.53)	

Panel C: $CRV_{i,t}^{BS}$

	# Months	*Average # Bonds*	α	β_{CRV}	β_{UMD}	β_{UMD2}	β_{BTM}	β_{SIZE}	$\beta_{E/P}$	β_{BETA}	**Adjusted R2**
t+1	149	457	-0.0014	0.0033	0.0156	0.0197	0.0020	-0.0005	-0.0023	0.0006	0.0796
			(-0.47)	(6.83)	(7.46)	(2.36)	(3.02)	(-1.62)	(-1.2)	(1.23)	
t+2	148	436	-0.0067	0.0019	0.0069	0.0240	0.0003	0.0005	-0.0013	-0.0006	0.0622
			(-2.55)	(3.75)	(2.9)	(2.77)	(0.52)	(1.72)	(-0.65)	(-1.12)	
t+3	147	420	-0.0024	0.0007	0.0039	0.0145	0.0002	0.0001	0.0000	-0.0009	0.0538
			(-0.9)	(1.37)	(1.73)	(1.7)	(0.3)	(0.35)	(-0.02)	(-1.64)	
t+4	146	406	-0.0029	0.0008	0.0028	0.0097	-0.0014	0.0002	0.0013	-0.0003	0.0527
			(-1.1)	(1.65)	(1.04)	(1.17)	(-1.84)	(0.67)	(0.59)	(-0.57)	
t+5	145	392	-0.0028	0.0004	0.0036	0.0180	0.0015	0.0002	0.0005	-0.0013	0.0505
			(-1.02)	(0.81)	(1.44)	(2.27)	(1.73)	(0.61)	(0.22)	(-2.09)	
t+6	144	379	-0.0028	0.0007	0.0014	0.0063	0.0010	0.0002	-0.0011	-0.0012	0.0465
			(-1.01)	(1.64)	(0.5)	(0.81)	(1.07)	(0.84)	(-0.54)	(-2)	

Panel D: $CRV_{i,t}^{EDF}$

	# Months	*Average # Bonds*	α	β_{CRV}	β_{UMD}	β_{UMD2}	β_{BTM}	β_{SIZE}	$\beta_{E/P}$	β_{BETA}	**Adjusted R2**
t+1	149	402	0.0037	0.0022	0.0156	0.0272	0.0014	-0.0012	-0.0037	0.0023	0.0715
			(1)	(9.1)	(7.27)	(3.93)	(2.09)	(-3.29)	(-1.99)	(3.68)	
t+2	148	384	-0.0035	0.0013	0.0073	0.0248	-0.0004	0.0001	-0.0064	0.0006	0.0567
			(-1.03)	(4.92)	(3.34)	(3.43)	(-0.54)	(0.32)	(-2.26)	(0.92)	
t+3	147	370	-0.0020	0.0013	0.0022	0.0112	0.0004	-0.0001	-0.0008	-0.0001	0.0506
			(-0.56)	(4.63)	(0.96)	(1.56)	(0.5)	(-0.37)	(-0.32)	(-0.09)	
t+4	146	357	-0.0033	0.0015	-0.0003	0.0068	-0.0007	0.0000	-0.0017	0.0005	0.0502
			(-0.95)	(5.33)	(-0.12)	(0.91)	(-0.93)	(-0.08)	(-0.67)	(0.86)	
t+5	145	345	-0.0029	0.0011	0.0036	0.0095	0.0023	0.0000	-0.0025	-0.0007	0.0488
			(-0.77)	(3.39)	(1.47)	(1.19)	(2.49)	(0.07)	(-1.02)	(-1.10)	
t+6	144	334	-0.0033	0.0010	0.0010	0.0071	0.0015	0.0001	-0.0038	-0.0007	0.0465
			(-0.88)	(3.12)	(0.39)	(0.90)	(1.66)	(0.39)	(-1.67)	(-0.95)	

Equation (14) is estimated for each month in the sample (149 months from January 1997 to May 2009), for K= 1 to 6, i.e. using the one to six months ahead returns as dependent variable. The equation is estimated using weighted least squares with the weights computed as $-\ln(CS_{i,t})$. Variable definitions are provided in the appendix.

Table 7

Economic significance

Future credit returns across $CRV_{i,t}$ quintiles

([-ln($CS_{i,t}$) weighted] portfolio returns)

Panel A: $CRV_{i,t}^{D2D}$

Quintile	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	-0.0043	-0.0019	0.0001	-0.0012	-0.0015	-0.0004
2	-0.0014	-0.0021	-0.0009	-0.0012	-0.0010	-0.0015
3	0.0006	-0.0009	-0.0010	-0.0006	-0.0005	-0.0005
4	0.0008	0.0006	0.0002	-0.0001	0.0005	0.0000
Top	-0.0006	0.0014	0.0000	0.0008	0.0000	0.0005
Hedge	0.0041	0.0038	0.0007	0.0024	0.0019	0.0013
FM T-stat	5.13	5.03	0.89	2.99	2.31	1.71
Sharpe	1.46	1.43	0.25	0.86	0.66	0.49

Panel B: $CRV_{i,t}^{BCM-BOTH}$

Quintile	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	-0.0035	-0.0023	-0.0014	-0.0017	-0.0014	-0.0011
2	-0.0014	-0.0010	-0.0006	-0.0008	-0.0003	0.0006
3	-0.0015	-0.0001	-0.0005	0.0001	-0.0001	-0.0005
4	-0.0001	0.0004	0.0005	0.0002	0.0001	-0.0007
Top	0.0019	0.0009	0.0013	0.0011	0.0000	0.0002
Hedge	0.0059	0.0036	0.0032	0.0030	0.0019	0.0017
FM T-stat	6.47	4.80	4.19	3.81	2.40	2.20
Sharpe	1.84	1.37	1.20	1.09	0.69	0.63

Panel C: $CRV_{i,t}^{BS}$

Quintile	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	-0.0045	-0.0020	-0.0009	-0.0005	-0.0015	-0.0009
2	-0.0026	-0.0018	-0.0008	-0.0010	-0.0005	-0.0011
3	-0.0007	-0.0005	-0.0005	-0.0002	0.0000	0.0003
4	0.0009	0.0007	0.0002	-0.0001	0.0002	-0.0001
Top	0.0031	0.0017	0.0006	0.0005	-0.0005	0.0004
Hedge	0.0077	0.0042	0.0020	0.0015	0.0013	0.0012
FM T-stat	8.60	4.56	2.26	1.75	1.51	1.62
Sharpe	2.44	1.30	0.65	0.50	0.43	0.47

Panel D: $CRV_{i,t}^{EDF}$

Quintile	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	-0.0031	-0.0016	-0.0016	-0.0014	-0.0012	-0.0012
2	-0.0015	-0.0005	-0.0008	0.0000	-0.0003	-0.0005
3	-0.0002	0.0004	-0.0001	-0.0002	-0.0001	-0.0002
4	-0.0001	0.0003	0.0009	0.0000	0.0003	0.0007
Top	0.0009	0.0005	0.0009	0.0012	0.0008	0.0007
Hedge	0.0044	0.0026	0.0029	0.0027	0.0019	0.0017
FM T-stat	3.31	2.16	2.43	2.08	1.46	1.35
Sharpe	0.94	0.61	0.69	0.60	0.42	0.39

For each sample month, bonds are sorted into five equal sized groups based on $CRV_{i,t}^{D2D}$, $CRV_{i,t}^{BCM-BOTH}$, $CRV_{i,t}^{BS}$, and $CRV_{i,t}^{EDF}$. RET1 to RET6 are the average returns for bonds within each of these groups one to six months ahead. The hedge return is the difference between the average portfolio return across extreme quintiles. The Fama-McBeth t-statistic for hedge returns is reported, as well as the Sharp ratio, calculated following Lewellen (2010). Variable definitions are provided in the appendix.

Table 8
Ex Post Return Analysis (Fama-French)

$$R^{CRV}{}_t = \alpha + \beta^{dRP} dRP_t + \beta^{dTS} dTS_t + \beta^{dVIX} dVIX_t + \beta^{dVIX} dVIX_t + \beta^{dIP} dIP_t + \beta^{MKT} R^{MKT}{}_t + \beta^{SMB} SMB_t + \beta^{HML} HML_t + \beta^{MOM} MOM_t + \varepsilon_t \quad \textbf{(15)}$$

	$CRV_{i,t}^{D2D}$	$CRV_{i,t}^{BCM-BOTH}$	$CRV_{i,t}^{BS}$	$CRV_{i,t}^{EDF}$
α	0.0045	0.0058	0.0080	0.0043
	(7.7)	(7.85)	(8.99)	(5.22)
β^{dRP}	0.0110	0.0134	-0.0053	0.0336
	(3.38)	(3.25)	(-1.08)	(7.32)
β^{dTS}	0.0068	0.0089	0.0134	0.0021
	(1.67)	(1.73)	(2.18)	(0.36)
β^{dVIX}	0.0002	0.0001	-0.0006	0.0003
	(1.15)	(0.42)	(-1.89)	(0.94)
β^{dIP}	-1.0267	-0.7956	-0.3283	-0.6461
	(-5.35)	(-3.27)	(-1.13)	(-2.39)
β^{MKT}	-0.0008	-0.0007	0.0000	-0.0012
	(-4.78)	(-3.33)	(-0.07)	(-5.29)
β^{SMB}	-0.0002	0.0000	-0.0002	-0.0003
	(-0.94)	(0.07)	(-0.94)	(-1.36)
β^{HML}	-0.0007	-0.0004	-0.0005	-0.0008
	(-3.72)	(-1.73)	(-1.98)	(-3.19)
β^{MOM}	0.0000	0.0003	0.0001	0.0004
	(-0.08)	(2.31)	(0.48)	(2.71)
Sharpe Ratio	2.19	2.23	2.55	1.48
Adjusted R^2	0.51	0.38	0.10	0.64

R^{CRV} is the hedge return for the month ending in t, calculated as the difference in the average portfolio return across extreme quintiles of CRV_{t-1} (from table 7). All remaining variables are defined in the appendix.

The Sharpe ratio is calculated as the ratio of the annualized return (as measured by the intercept) relative to the annualized standard deviation. As Lewellen (2010) notes this is a simple transformation of the t-statistic and is computed as the t-statistic multiplied by $\sqrt{12}$ divided by $\sqrt{149}$, where 149 reflects the number of months in the regression.