Credit Risk Neglect

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Abstract

I study how the pricing of credit risk varies over time in corporate bond and equity markets. I introduce a new measure of credit market sentiment, yield-for-risk (YFR_t), which captures the cross-sectional sensitivity of corporate bond spreads to default risk. When YFR_t is high, riskier bonds and stocks earn higher subsequent returns, consistent with a positive risk–return relationship. When YFR_t is low, credit spreads are insensitive to risk, and the risk–return relationship inverts: securities issued by riskier firms earn lower future returns than those issued by safer firms in both the corporate bond and equity markets. The simultaneous inversion across asset classes suggests investors overestimate the fundamental value of corporations leading them to neglect the credit risk associated with their capital structure. Periods of low YFR_t are preceded by low default rates, loosening lending standards, and high past returns, and coincide with increased debt issuance concentrated among the riskiest issuers. I present an equilibrium model with extrapolative beliefs that accounts for the empirical patterns across debt and equity markets.

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1 Introduction

A core principle in financial economics is that investors demand higher expected returns for bearing greater risk. However, while corporate bankruptcy represents the most fundamental risk to investors' capital, the empirical relationship between credit risk and average returns is weak (Dichev, 1998; Campbell et al., 2008). In this paper, I show that the weak average relationship masks a pronounced and predictable time series variation in the compensation for credit risk, which is present in both corporate bonds and stocks. Using a newly constructed panel of bond and stock returns, I introduce a novel measure of credit-market sentiment, the yield-for-risk (YFR_t), and show that it forecasts the pricing of credit risk in both markets. Strikingly, the compensation for credit risk switches sign: it is positive when markets price credit risk steeply and negative when markets are sanguine. This predictable inversion of the risk-return relationship occurs simultaneously in corporate bonds and points to systematic neglect of credit risk by investors during market booms. I reconcile the findings in an equilibrium model in which a representative investor forms extrapolative beliefs about firm fundamentals.

The central innovation of the paper is YFR_t, a simple and transparent measure of the cross-sectional price of credit risk. At each date, YFR_t is the average incremental yield investors require to move one standard deviation closer to default in the cross-section of corporate bonds. To estimate YFR_t, I construct a panel of investment-grade corporate bonds from January 1976 through July 2024 by combining the Lehman/Warga database, the ICE Fixed Income database, and TRACE. I then regress the cross-section of credit spreads on the cross-section of risk at each date, where risk is measured by (the negative of) distance-to-default.[1]

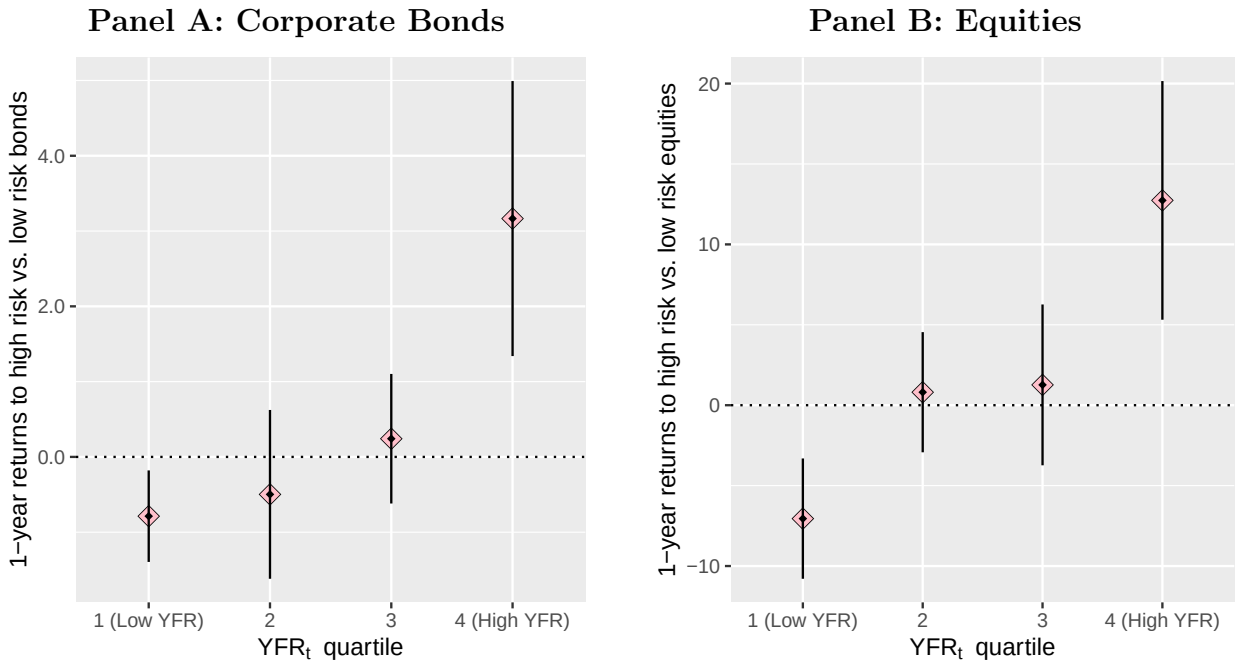
A key advantage of YFR_t is its economic interpretability: low values correspond to periods in which credit spreads are unusually insensitive to default risk. For example, in May 2007, YFR_t equals 0.01%, implying that investors require only 0.01% in additional yield for moving one standard deviation closer to default. Given that expected losses provide a lower bound for credit spreads, a YFR_t of 0.01% also implies that investors perceive the associated increase in expected losses to be at most 0.01%. By March 2009, YFR_t had risen almost thirty-fold to 0.29%. While the Global Financial Crisis is a salient example, similar boom–bust dynamics appear throughout the sample.

Figure 1 summarizes the central empirical pattern. Average returns on long–short portfolios that load on credit risk are negative when YFR_t is in its lowest quartile and positive when YFR_t is in its highest quartile. This state dependence is present in both the corporate

[1] Distance-to-default is measured empirically using the methodology of Bharath and Shumway (2008).

bond market (Panel A) and the equity market (Panel B).

Figure 1. The Risk–Return Relation Conditional on Yield-for-Risk



This figure reports average one-year returns to portfolios that are long the 20% riskiest assets and short the 20% safest assets (as measured by distance-to-default), conditional on the level of yield-for-risk (YFR_t). "Low" ("High") YFR_t corresponds to the bottom (top) quartile of its empirical distribution; intermediate bars correspond to the second and third quartiles. Bars denote 95% confidence intervals computed using Newey–West standard errors with 18 lags and fixed-b asymptotics following Kiefer and Vogelsang (2005).

Using YFR_t, I document four empirical results. First, YFR_t predicts returns to credit risk in the cross-section of corporate bonds. I measure the bond return spread as the return difference between bonds issued by the 20% riskiest firms and the 20% safest firms, where risk is measured by distance-to-default. A one-standard-deviation decline in YFR_t reduces the expected return on the risky-minus-safe bond portfolio by 0.15% over the next month.

Second, the same pattern holds in equities. A one-standard-deviation decline in YFR_t lowers expected returns on the risky-minus-safe equity portfolio by 0.74% over the next month. Predictability strengthens with horizon, reaching 1.8% for the bond portfolio and 7.9% for the equity portfolio at the 12-month horizon.

Third, YFR_t predicts returns to credit risk in the time series of the aggregate corporate bond market. Controlling for changes in the term structure of Treasury yields, I show that predictability reflects time variation in the price of credit risk rather than predictable movements in risk-free rates. Consistent with the cross-sectional evidence, periods of low YFR_t forecast negative credit compensation in the aggregate market.

Fourth, YFR_t predicts issuer behavior. Firms increase net debt issuance following low-YFR_t periods, with effects concentrated among the riskiest issuers. A one-standard-deviation decline in YFR_t is associated with a 0.31% increase in net debt issuance relative to assets over the next quarter. When YFR_t is in its lowest quartile, the riskiest 20% of firms increase issuance by 0.8% of assets, while the safest firms exhibit little response. Thus, when credit spreads become less sensitive to credit risk, aggregate debt issuance rises and the composition of issuance tilts toward riskier firms.

Across specifications, the predictive content of YFR_t is not subsumed by standard credit spreads or prominent measures of credit-market sentiment, including the excess bond premium of Gilchrist and Zakrajšek (2012) and the high-yield share of Greenwood and Hanson (2013). The results are also robust to alternative portfolio constructions and to small-sample biases such as the Stambaugh (1999) bias.

While time-varying risk premia are consistent with canonical asset-pricing models (Campbell and Cochrane, 1999; Bansal and Yaron, 2004), a predictable inversion of the risk–return relationship is difficult to reconcile with rational expectations. To interpret the evidence, I develop an equilibrium model in which a risk-averse representative investor extrapolates news about firm fundamentals. Firms issue both debt and equity, priced as contingent claims on firm assets following Merton (1974). Extrapolative beliefs enter via diagnostic expectations (Bordalo et al., 2018), generating excessive optimism after good news and excessive pessimism after bad news. In equilibrium, extrapolation compresses YFR_t and implies negative expected compensation for credit risk following good news, in both bonds and stocks. The inversion is stronger for equities, consistent with the empirical evidence that equity is more information-sensitive than corporate debt.

Related Literature. This paper relates to several strands of the literature on credit risk, asset pricing, and investor sentiment.

First, it builds on the extensive literature documenting the weak relationship between credit risk and average returns, commonly referred to as the distress anomaly. Early studies show that stocks of financially distressed firms earn low average returns despite their elevated default risk (Dichev, 1998; Griffin and Lemmon, 2002; Campbell et al., 2008). Subsequent work demonstrates that this pattern extends beyond equities to corporate bonds (Avramov et al., 2022). I contribute to this literature by showing that returns to credit risk are strongly time-varying and predictable, and that periods of low compensation for credit risk are characterized by an inversion of the risk–return relationship in both bond and stock markets.

Second, the paper relates to the literature studying the determinants of corporate bond spreads and their connection to firm fundamentals. A large body of work documents that

credit spreads are only weakly explained by default risk measures (Elton et al., 2001; Collin-Dufresne et al., 2001; Longstaff et al., 2005; Huang and Huang, 2012). While prior studies emphasize the role of liquidity, volatility, and other non-default components of spreads, this paper focuses on the cross-sectional sensitivity of credit spreads to credit risk. By estimating this sensitivity directly, I document that the pricing of credit risk varies sharply over time, with some periods exhibiting a tight link between spreads and fundamentals and others showing an almost complete disconnect.

Third, this paper contributes to the growing literature on credit market sentiment and return predictability. Prior work shows that measures such as the excess bond premium (Gilchrist and Zakrajšek, 2012) and issuer quality (Greenwood and Hanson, 2013) predict bond and stock returns, as well as firm issuance behavior. I complement this literature by introducing yield-for-risk, a measure that captures the time-varying cross-sectional price of credit risk rather than the overall level of credit spreads. Consistent with this distinction, yield-for-risk contains predictive power for returns to credit risk in both bonds and equities that is not subsumed by existing sentiment measures.

Fourth, the paper relates to evidence that credit market conditions affect firms' financing decisions. Previous studies document that periods of easy credit are associated with increased issuance and a shift toward riskier borrowers (Greenwood and Hanson, 2013; Baron and Xiong, 2017; Fahlenbrach et al., 2018). I show that low values of yield-for-risk predict increases in net debt issuance driven primarily by the riskiest firms, linking variation in the pricing of credit risk to real financing outcomes.

Finally, the paper speaks to theories of investor beliefs and expectation formation. While time-varying risk premia are consistent with standard asset pricing models (Campbell and Cochrane, 1999; Bansal and Yaron, 2004), these models struggle to explain predictable inversions of the risk–return relationship. I interpret the evidence through a model of extrapolative expectations, building on diagnostic expectations (Bordalo et al., 2018), in which investors overreact to recent news and underweight downside risk following good outcomes. The model provides a unified explanation for the joint behavior of bond and equity returns and distinguishes extrapolative beliefs from rational-expectations alternatives.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 details the construction of YFR_t. Section 4 presents the empirical results. Section 5 develops the model. Section 6 concludes. The appendix contains proofs and additional empirical results and robustness tests.

2 Data

I construct a panel of corporate bond returns and yields using information from three databases. The first database is the Lehman/Warga database, which provides monthly information – including yields, returns, maturities, and ratings – on the publicly traded, nonconvertible bonds in the Lehman Brothers Bond Indices from January 1973 to March 1997. Returns are calculated from lot bid prices, which are based on either actual dealer quotes or "matrix prices" calculated from the dealer quotes on resembling bonds. I include only bonds with yields and returns based on actual dealer quotes in my sample.[2] The second bond database is the ICE Fixed Income platform, which provides daily data on the constituents on the ICE Bank of America Fixed Income Indices (formerly known as the Bank of America-Merrill Lynch Global Research FICC index platform) starting in December 1996. The database includes information on returns, yields, and bond-level characteristics such as duration and ratings. The third database is the WRDS Corporate Bond Panel, which compiles information from the TRACE Standard database and the TRACE enhanced database to construct a monthly panel of returns, yields, and bond characteristics for all corporate bonds traded since July 2002.[3] To estimate the credit spread of each bond in the panel, I subtract the yield of a synthetic zero-coupon Treasury bond with duration equal to that of the corporate bond. I obtain data on the U.S. Treasury yield curve from The Federal Reserve Board (Gürkaynak, Sack, and Wright, 2007) and estimate the yield of the synthetic Treasury bond using linear interpolation.[4]

I complement the databases listed above with information from Mergent FISD on special bond characteristics such as callability, convertibility, and sinking-fund provisions, when these are not provided. Further, I add information on the companies' monthly equity returns and market capitalizations from CRSP. Lastly, I add information on quarterly and annual financial statements of the issuers using Compustat Fundamentals. Given that financial statements are not reported at a monthly frequency, I include the most recently available book data within a year.

I splice the three corporate bond databases to construct a monthly panel of bond yields

[2]See Gebhardt, Hvidkjaer, and Swaminathan (2005) and Hong and Warga (2000) for more details on this database.

[3]See https://wrds-www.wharton.upenn.edu for more information.

[4]For a given maturity m^* the synthetic Treasury yield $y^f_{m^*}$ is found as:

$$y^f_{m^*} = y_{\underline{m}} + \frac{y^f_{\overline{m}} - y^f_{\underline{m}}}{\overline{m} - \underline{m}}(m^* - \underline{m})$$

where $\underline{m}$ is the longest duration less that m^* for which we have data on Treasury yields. Similarly, $\overline{m}$ is the shortest duration greater than m^* for which we have data on Treasury yields.

and returns along with the firm level characteristics and stock returns from 954 different firms starting in January 1976 and ending in July 2024.[5] My sample consists of senior investment-grade bonds (BAA3 and higher on Moody's rating scale) from the Lehman/Warga database (January 1976 to December 1996), the ICE Bank of America Fixed Income Indices (January 1997 to June 2002), and the WRDS (TRACE) Corporate Bond Panel (July 2002 to July 2024). I include bonds with time to maturity greater than 2 years issued by non-financial firms with a market capitalization of more than $50 million in 2016 real terms.[6] I exclude all convertible and putable bonds along with bonds with sinking fund provisions in order to better identify the relationship between credit risk and credit spreads. I further exclude speculative-grade bonds from my main analysis for several reasons. First, by looking only at investment-grade bonds, I minimize potential obfuscation stemming from differences in liquidity, which is known to be an important determinant of credit spreads among speculative-grade bonds, but less so among investment-grade bonds.[7] Further, by excluding speculative-grade bonds I keep the composition of my sample as homogeneous as possible over time, meaning my results are not affected by, e.g., the growth in speculative-grade bonds experienced during the 1980's. Therefore, looking only at investment-grade bonds, allows me to better estimate the price of risk as opposed to the changing composition of the corporate bond market. Lastly, focusing on investment-grade bonds potentially aids in the detection of credit risk neglect as the external endorsement of an investment-grade rating may cause investors to ignore the underlying risks.

Returns, yields, and firm characteristics such as distance-to-default are all winsorized at the 1% level. My final panel consists of monthly observations at the bond-level, which means I allow firms to enter the panel with multiple bonds. I do this to better correct for bond characteristics such as duration and callability.[8] Summary statistics for my sample can be found in Table 1.

[5]While the Lehman/Warga database starts in 1973 there are very few actual quotes before 1976, which is the reason my sample starts here. The number of unique firms is identified using the `permco` identifier from CRSP.

[6]Non-financial firms are defined as firm's with SIC codes outside the range 6000-6799.

[7]Feldhütter and Schaefer (2018) find no relation between liquidity and bond yields among investment-grade bonds from 1987-2012. Similarly, Dick-Nielsen et al. (2012) finds liquidity to have little effect on investment-grade bond yields outside the 2008 financial crises.

[8]An alternative approach is to aggregate returns and yields to firm level, effectively creating one hybrid bond for each firm. There is precedent for both approaches in the literature (Bessembinder et al., 2009), but my results are not sensitive to the approach used.

3 Measuring Sentiment: Yield-for-Risk

In order to estimate investors appetite for credit risk, I introduce novel measure of credit market sentiment, which captures how much credit spreads fluctuate with credit risk in the cross-section of bonds at a given point in time. Specifically, I measure the additional yield required by investors when a firm moves one standard deviation closer to default. I denote this measure yield-for-risk (YFR_t), and I estimate it by regressing credit spreads on distance-to-default at each point in time:

$$y_{ijt} - y^f_{jt} = \alpha_t + YFR_t \times (-DD_{it}) + \gamma_t' Z_{ijt} + \epsilon_{ijt}. \tag{1}$$

Here, y_{ijt} is the time-t yield of bond j issued by firm i, and y^f_{jt} is the yield of a zero-coupon Treasury bond with maturity equal to the duration of bond j. Subtracting the Treasury yield ensures that YFR_t is measuring compensation for risk and is not contaminated by the term structure of risk-free rates. Risk is measured by a firm's distance-to-default and is estimated following the methodology of Bharath and Shumway (2008):

$$DD_{it} = \frac{\log\left((ME_{it} + F_{it})\right) + r_{it-1} - 0.5\sigma^2_{it} - \log(F_{it})}{\sigma_{it}}, \tag{2}$$

where ME_{it} is the market value of the firm's equity, F_{it} is the face value of the firm's debt, r_{it-1} is the return on the firm's stock over the past year, and σ_{it} is the volatility of the firm's assets.[9] A high DD_{it} means a firm is safe, as it has low leverage relative to the volatility of its underlying assets and therefore little risk of default. Vice versa, a low DD_{it} means the firm is relatively close to its default barrier, F_{it}, and thus risky. The vector Z_{ijt} contains the control variables: the (log) duration of the bond, the size of the issuer, the age of the bond, and an indicator variable that equals one if bond j is callable.[10] I include duration to account for the term structure of credit spreads, while issuer size is included to mitigate the potential differences in liquidity between bonds issued by larger firms and bonds issued by smaller firms. Similarly, bond age is included as a control variable to account for potential differences in liquidity between newly issued bonds and seasoned bonds. Lastly, I control for callability to account for the time-varying value of the option to redeem the bond early.[11]

[9] The face value of debt is approximated by a firm's current liabilities plus one-half the firm's long-term liabilities (`dlcq`+0.5×`dlttq`). The volatility of the firm's assets is estimated as $\sigma_{it} = E_{it}/(E_{it} + F_{it})\sigma^E_{it} + F_{it}/(E_{it} + F_{it})(0.05 + 0.25\sigma^E_{it})$, where σ^E_{it} is the annualized volatility of the firm's monthly stock return over the past year.

[10] Issuer size is defined as the log of total assets (`atq`), and bond age is defined as the (log) number of years the bond has been in my panel.

[11] For example, Duffee (1998) documents the time-varying value of the option embedded in a callable bond.

Figure 2 presents the time-series plot of YFR_t. A strength of YFR_t as a measure of sentiment is that it easily identifies periods where investors are insensitive to risk. For example, in May of 2007, immediately prior to the financial crisis, YFR_t reaches levels as low as 0.01%, which means the investors require just 1 basis point more in yield for holding a bond that is one standard deviation closer to default. Given that the cross-sectional standard deviation in distance-to-default is 6.3 in May, 2007, a YFR_t of 0.01% corresponds to investors requiring just 0.15% more in yield when distance-to-default falls by two standard deviations. In contrast, during the Global Financial Crisis in March, 2009, YFR_t reaches 0.29%, meaning investors on average require 29 basis points in additional yield when a bond moves a standard deviation closer to default. Given that the cross-sectional standard deviation in distance-to-default is 3.3 in March 2009, a YFR_t of 0.29% corresponds to investors requiring 1.9 percentage points more in yield when distance-to-default falls by two standard deviations.

Episodes of low YFR_t are particularly interesting given that the credit spread of a bond must at least compensate the investor for the bond's expected loss. This means that in May of 2007, investors expect losses to increase by at most 0.01% when a bond moves one standard deviation closer to default. To be clear, this may be rational, and YFR_t cannot ex ante reject that investors are correctly assessing the risk of the bond market. YFR_t simply provides a bound on the beliefs investors must have about the relationship between risk and expected losses in the cross-section of corporate bonds.

To understand what characterizes periods of high and low yield-for-risk, I regress YFR_t on four variables, which capture the state of the economy and the current sentiment in the market. The first variable is the issuer-weighted default rate of corporations obtained from Moody's Investors Service in a given year, the second is the net fraction of banks reporting tighter lending standard minus the fraction of banks report looser lending standards in the Federal Reserve's Senior Loan Officer Opinion Survey in a given quarter, the third is the excess return on the corporate bond market over the past three years (annualized), and the fourth is the excess return on the stock market over the past three years (annualized). Table 2 presents the results. Yield-for-risk is scaled to basis points (bp) in the regressions such that a coefficient of 2.09 in Column 1 means that a 1% lower default rate in a given year is associated with a 2.09 bp lower YFR_t by the end of the year. Similarly, a quarter where the fraction of banks reporting tightening lending standards minus the fraction of banks reporting loosening lending standard falls by 1% is succeeded by a 0.12 bp lower YFR_t at the end of the quarter. Lastly, a 1% higher annual excess bond market return over the past three years, or a 1% higher annual excess stock market return over the past three years is followed by a 0.15 bp, and 0.36 bp, lower YFR_t, respectively. In summary, we see that low YFR_t is preceded by low default rates among corporates, loosening lending standards, and

high returns in both the bond and stock markets. The results are consistent with the notion that periods of low yield-for-risk are periods where investors regard the bond market as being fairly safe based on the past performance of bonds and the markets in general.

Although structural models of credit risk imply that credit spreads are a nonlinear function of distance-to-default (Merton, 1974), my goal is not to recover the full cross-sectional mapping from distance-to-default to spreads. Instead, I use a linear projection as a parsimonious way to summarize, at each date, how strongly spreads price default risk in the cross section. The resulting slope, YFR_t, has a direct interpretation as the incremental yield investors require for moving one standard deviation closer to default. Figure 3 illustrates that the strength of the spread–risk relation varies substantially over time, but that a linear approximation captures the dominant cross-sectional pattern in the data. Consistent with this, excluding DD_{it} from (1) lowers the (within) R^2 from 36% to 19%.Allowing for curvature by adding DD_{it}^2 increases the R^2 by only 5%. Moreover, the incremental contribution of the squared term is negligible precisely in the episodes of primary interest: when YFR_t is low.[12] Importantly, including DD_{it}^2 leaves the time-series behavior of YFR_t and its return-forecasting results essentially unchanged. I therefore retain the linear specification, which delivers a transparent and comparable measure of the cross-sectional price of credit risk over time. Introducing higher-order terms would modestly improve in-sample fit but at the cost of interpretability.

4 Empirical Implementation and Results

4.1 Predicting Returns to Credit Risk in the Cross-Section

If YFR_t captures time variation in how investors price credit risk, then it should predict subsequent returns to credit risk in both bonds and equities. In particular, it should predict the returns of the riskiest bonds over the safest bonds, and the riskiest equities over the safest equities. To test the hypothesis that YFR_t predicts the cross-section of bond returns, I construct a self-financing portfolio with monthly rebalancing, which is long the bonds of the riskiest firms at time t (i.e. the firms with the lowest distance-to-default), and short the bonds of the safest firms (i.e. the firms with the highest distance-to-default). Formally, let k_t denote the number of bonds in my panel at time t and define the h-month return to the

[12]When YFR_t is in its lowest quartile, adding DD_{it}^2 raises the within R^2 by less than 2%.

$n\%$ riskiest bonds as:

$$r_{t+h}^{n\% \ riskiest} = \sum_{j=1}^{k_t} w_{jt} r_{ijt+h} 1_{\{\widetilde{DD}_{it} < n^{th} \text{ percentile}\}} \tag{3}$$

Here, r_{ijt+h} is the h-month return on the bond j issued by firm i from time t to time $t+h$, $1_{\{\widetilde{DD}_{it} < n^{th} \text{ percentile}\}}$ is an indicator variable, which equals one if firm i is among the $n\%$ riskiest firms at time t, meaning it has a distance-to-default which is below the n'th percentile at time t. w_{jt} is the portfolio weight of bond j, i.e. the fraction of the portfolio invested in bond j. Similarly, I define the return to the $n\%$ safest bonds as:

$$r_{t+h}^{n\% \ safest} = \sum_{j=1}^{k_t} w_{jt} r_{ijt+h} 1_{\{\widetilde{DD}_{it} > (100 - n^{th}) \text{ percentile}\}} \tag{4}$$

For my baseline analysis, I use equal-weighted returns $w_{jt} = (\sum_{h=1}^{k_t} 1_{\{\widetilde{DD}_{ht} < n^{th} \text{ percentile}\}})^{-1}$, and include the 20% riskiest firms in the high-risk portfolio and the 20% safest firms in the low-risk portfolio ($n = 20$).[13] I then estimate the forecasting model:

$$r_{t+h}^{20\% \ riskiest} - r_{t+h}^{20\% \ safest} = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \epsilon_{t+h} \tag{5}$$

where $r_{t+h}^{20\% \ riskiest} - r_{t+h}^{20\% \ safest}$ is the h-month return to the 20% riskiest corporate bonds over the 20% safest corporate bonds, and YFR_t is the yield-for-risk parameter estimated from equation (1) normalized by its standard deviation. The vector X_{t+h} contains the change in the level of the 10-year Treasury yield, and the change in the slope of the Treasury yield curve, measured as the difference between the 10-year and the 1-year Treasury yield, as control variables. The changes in the level and slope of the Treasury yield curve are measured contemporaneously with the returns of the long-short bond portfolio, and are included to ensure that any predictability detected stems for the repricing of credit risk, and not changes in the risk-free rate, which is the other key determinant of bond returns.

Panel A of Table 3 presents the results of predicting returns to credit risk in the cross-section of corporate bonds at the 1-, 6- and 12-month horizon. We see that YFR_t significantly predicts returns to the cross-section of bonds consistent with the interpretation of YFR_t as a measure of bond market sentiment: when YFR_t is high the expected return on risky bonds over safe bonds is high and positive, and when YFR_t is low, the expected return on risky bonds over safe bonds is low. The effect is statistically and economically significant, and

[13] In the robustness analysis below I show that my results are robust to different specifications of weights w_{jt} and portfolio inclusion criteria n.

grows substantially with the prediction horizon. A one standard deviation increase in yield-for-risk leads to a 15 basis point increase in the average returns of the riskiest bonds over the safest bonds over the following month, a 1.1% increase in average returns over the following 6-months, and 1.8% increase over the following 12-months. The predictability remains significant and virtually unchanged in magnitude when controlling for contemporaneous changes in the level and slope of the Treasury yield curve, which indicates that YFR_t is in fact predicting changes in the price of credit risk. In order to account for autocorrelation and heteroskedasticity in the regression residuals, I use Newey and West (1987) standard errors with 0, 9 and 18 monthly lags at the 1-, 6- and 12-month prediction horizon, respectively, to assess the statistical significance of the regression coefficients. I calculate p-values using "fixed-b" asymptotics of Kiefer and Vogelsang (2005) to tackle the well-known issue that t-statistics based on Newey and West (1987) standard errors tend to over-reject in finite samples.

Panel B of Table 3 repeats the prediction exercise outlined above, but with equity returns replacing bond returns. That is, I construct a self-financing portfolio with monthly rebalancing which is long equities from riskiest quintile of firms, and short equities from the safest quintile of firms. The sensitivity of equity returns to YFR_t is substantially larger than that of bond returns, consistent with equity being more exposed to fluctuations in perceived credit risk. Specifically, a one standard deviation increase in YFR_t leads to a 74 basis point increase in the average returns of the riskiest equities over the safest equities over the following month, a 4.5% increase in average returns over the following 6-months, and 7.9% increase over the following 12-months. Once again we see that controlling for changes in the level and slope of the Treasury yield curve does not materially alter the results.

I test the novelty of YFR_t as a measure of credit risk sentiment by running a horse race of YFR_t as a predictive variable against other well-known measures of credit market sentiment; Excess Bond Premium (EBP) of Gilchrist and Zakrajšek (2012), the *High Yield Share* (HYS) of Greenwood and Hanson (2013), and the CBOE VIX index. The EBP is designed to capture the risk premium in corporate bonds, i.e. the compensation for *"... bearing exposure to US corporate credit risk, above and beyond the compensation for expected defaults."*, while the HYS measures the fraction of newly issued bonds issued by firms with a non-investment grade credit rating. The VIX is constructed to measure 30-day expected volatility from call options on the S&P500 index. Further, I test that the predictability reported in Table 3 is not subsumed by a standard credit spread such as the average difference in yields between BAA rated bonds and 10-year Treasury bonds. Table 4 shows that YFR_t maintains its predictive power in light of the inclusion of any of the other sentiment measures.[14] Further,

[14]The predictive results are only reported on a 12-month basis for brevity, but are similar at 1-month

none of the other known measures of sentiment predict returns to the cross-section of bonds and stocks with any significance, when YFR_t is included in the regression. Note that the HYS is measured only at a quarterly frequency, while the VIX is only available from January 1990.

4.1.1 Robustness

I perform a series of additional test to alleviate concerns about the robustness of the predictability documented above. First, I show that my results are not sensitive to the specification of the portfolios. Specifically, I reestimate the forecasting regression (5) across a range of different inclusion criteria: $n \in \{15, 20, 25, 30, 35\}$. That is, I predict the returns of the 15% riskiest bonds (and stocks) over the return of the 15% safest bonds (and stocks), the returns of the 20% riskiest bonds (and stocks) over the return of the 20% safest bonds (and stocks), and so forth. Further, in my baseline specification, I calculate portfolio returns with equal weight on every bond in the portfolio. As a consequence, my results might be driven by the smallest bonds and stocks and thus not representative of the market. I redo the prediction exercise of regression (5), but weight each bond by the amount outstanding to address this concern. Similarly, for equity returns, I weight each stock by the market capitalization of the firm.[15] Table A1 of the Appendix presents the results, showing that as I raise the criteria for entering the portfolio (lower n) the magnitude of the predictive coefficient naturally increases. E.g. if YFR_t falls by one standard deviation, the 12-month returns of the 15% riskiest bonds falls by 1.97% relative to the 15% safest (Panel A, line 1, second last column). In contrast, the returns of the 35% riskiest bonds falls by 1.30% relative to the 35% safest (Panel A, line 5, second last column). This pattern is true across prediction horizons, and is unaffected by changing the portfolio weights to reflect the amount outstanding. The same is true for the predictability of returns to the riskiest equities over the safest equities, as evident from Panel B. The shaded cells of the table indicate the baseline specifications presented in Table 3.

Another concern is that the duration of the portfolio changes over time, making the contemporaneous term structure controls included in regression (5) invalid. To address this

and 6-month prediction horizons. Further, the predictability survives the inclusion of a range of alternative sentiment measures such as the TED Spread (the spread between 3-month USD LIBOR and the 3-month Treasury Bill), the GZ Spread (the average credit spread of Gilchrist and Zakrajšek (2012)), and measures of expected stock market returns like the CAY measure of Lettau and Ludvigson (2001) and cyclically-adjusted price-earnings ratio (CAPE) of Shiller (2000).

[15] Formally, for bonds I let the weight parameter be: $w_{jt} = \frac{Amount\ Outstanding_{jt}}{\sum_h Amount\ Outstanding_{ht}}$, and for equities I let the weighing be $w_{it} = \frac{Market\ Capitalization_{it}}{\sum_h Market\ Capitalization_{ht}}$. I limit weights to be at most 20% such that no single firm or bond dominates the portfolios.

issue, I construct a hedged bond return by measuring the return of each bond in my panel in excess of the return on a synthetic Treasury bond with equal duration:

$$r_{ijt+h}^{bond,hedged} = r_{ijt+h}^{bond} - r_{t+h}^{f} \tag{6}$$

where r_{ijt+h}^{bond} is the return from t to $t+h$ on the bond j issued by firm i, and r_{t+h}^{f} is the return on a risk-free Treasury bond of equal duration to bond j from over the same period.

Table A1, Panel A in the Appendix presents the results of performing the forecasting regression (5) with standard bond returns replaced by the hedged bond returns defined in (6). We see that the predictive power of YFR_t on future bond returns is unaffected by the change in dependent variable, indicating that time-varying duration of the long-short portfolio is not driving the predictive relationship.

For equity returns there is not an obvious way to hedge against changes in the risk-free rate, since we do not know the duration of equities. Instead, I use a 36-month rolling window regression to estimate the sensitivity of the one-month equity return of each firm to the one-month return on a 10-year Treasury bond. That is, for each stock i at each date, $\bar{t}$, I regress the one-month equity return r_{it+1}^{stock} on the one-month return of a 10-year Treasury bond using data from $\bar{t}-36$ to $\bar{t}$ only:

$$r_{it+1}^{equity} = a + b_{i\bar{t}}\, r_{t+1}^{f} + e_t \quad \text{for } t \in [\bar{t}-36, \bar{t}] \tag{7}$$

I then calculate the h-month interest-rate hedged equity return of firm i, $r_{it+h}^{equity,hedged}$, as equity return of firm i, r_{it+h}^{equity}, minus the sensitivity of firm i's equity returns to Treasury returns, b_{it}, times the h-month return to the 10-year Treasury bond, r_{t+h}^{f}:

$$r_{it+h}^{equity,hedged} = r_{it+h}^{equity} - b_{it} r_{t+h}^{f} \tag{8}$$

Table A1 Panel B presents the results of the forecasting regression (5) with hedged equity returns as the dependent variable. We again see that the predictive power of YFR_t on future returns is unaffected by controlling for the changes in risk-free interest rates.

As a final robustness test, I address the concern that finite sample statistical issues may lead me to overstate the economic magnitudes of the predictability of returns due to Stambaugh (1999) bias, and the statistical significance of my results due to the tendency of asymptotic standard errors to over-reject in finite samples. The latter concern should be mitigated by the use of Kiefer and Vogelsang (2005) p-values throughout the paper, which are designed to handle this issue. As an additional robustness test, I use the stationary moving blocks bootstrap technique of Politis and Romano (1994) to construct 100,000 pseudo

samples, and apply a bootstrap-t procedure to obtain a non-parametric estimate of the p-values.[16] The success parameter applied in creating the pseudo samples is 1/12, meaning that average block length is 12 months, but the result is not sensitive to this specification. Table A3 presents a comparison of the p-values obtained using regular asymptotic theory and Newey and West (1987) standard errors, using the Kiefer and Vogelsang (2005) adjusted p-values, and finally the p-values obtained from the bootstrap-t procedure. I find virtually no difference in p-values between the methods indicating that finite sample bias is not obfuscating the statistical inference.

Further, Table A3 reports the standard bootstrap bias estimator, i.e. the difference between the coefficient estimate obtained in my original sample, and the average coefficient estimate of the 100,000 bootstrapped pseudo samples, and shows that bias in the coefficient estimates is negligible. To bolster this conclusion, I also present an analytical estimate of the Stambaugh (1999) bias using the method of Boudoukh et al. (2020) who develop a framework for calculating this bias in overlapping, long-horizon regression. The bias estimated from this analytical approach does not materially differ from the bias estimated using the bootstrap procedure, and I conclude that my results are not driven by small-sample biases.

4.2 Predicting Risk-Return inversion

Panel A and B of Table 3 both report statistically significant, negative intercepts across all specifications. This implies that as sentiment increases and YFR_t approaches zero, returns on the riskiest bonds and stocks significantly underperform those on the safest bonds and stocks. To formally test if low YFR_t predicts negative returns to risk, I split my time series in four based on the value of YFR_t. That is, I calculate the empirical distribution of YFR_t based on my full sample and assign all dates at which YFR_t is below the 25$^{\text{th}}$ percentile to one group, all dates at which YFR_t is between its 25$^{\text{th}}$ and 50$^{\text{th}}$ percentile to the next group, and so on. For each of these four groups, I then calculate the average 1-year return to the long-short bond and equity portfolios presented above. Figure 1 (shown in the Introduction to preview the main result) presents the results with confidence bands calculated using Newey and West (1987) standard errors with 18 lags and Kiefer and Vogelsang (2005) "fixed-b" asymptotics. We see that when YFR_t is in its lowest quartile, the risk-return relationship has significantly inverted as the riskiest bonds underperform the safest bonds by 0.8% over the following year. Further, the same result holds true in the equity market, where the riskiest equities underperform the safest equities by 7.4% over the following year. In contrast, when

[16] Greenwood, Hanson, Shleifer, and Sørensen (2022) applies the same non-parametric block bootstrap technique and provides a detailed description of the approach in Section D of their Internet Appendix. I refer to their paper for a more detailed description of the method applied here.

YFR_t is in its highest quartile, the riskiest bonds outperform the safest bonds by 3.2% over the following year, and the riskiest equities outperform the safest equities by 13.0% over the following 12 months, consistent with the idea that investors require a premium for holding riskier bonds and stocks. The inversion of the risk-return relationship during periods of low YFR_t suggests that investors systematically neglect the risks embedded in firms' capital structures when pricing risky firms' securities. The model in Section 5 shows that the simultaneous inversion of the risk-return relationship across bonds and stocks is consistent with investors being too optimistic about the fundamental value of the firms.

To show that the risk-return inversion documented in Figure 1 is not an artifact of the specification, I change both the criteria for entering the high- and low-risk portfolios, and the periods we consider as periods of high and low yield-for-risk, and redo the analysis above. Specifically, let $r_{t+12}^{n\%\ riskiest}$ be the average 12-month portfolio return on assets issued by firms with distance-to-default below the n'th percentile, and $r_{t+12}^{n\%\ safest}$ be the average 12-month returns on assets issued by firms with distance-to-default above the $(100-n)$'th percentile as defined in (3) and (4). Further, let $1_{\{YFR_t \leq m\text{'th percentile}\}}$, $1_{\{YFR_t > m\text{'th percentile}\}}$ and $1_{\{m\text{'th percentile} < YFR_t \leq (100-m)\text{'th percentile}\}}$ denote indicator variables that switch on if YFR_t is below its m'th percentile, above its $(100-m)$'th percentile, or in between its m'th and $(100-m)$'th percentile, respectively. I then estimate the regression model:

$$\begin{aligned} r_{t+12}^{n\%\ riskiest} - r_{t+12}^{n\%\ safest} = & \lambda^{Low} \times 1_{\{YFR_t \leq m\text{'th percentile}\}} + \\ & \lambda^{Mid} \times 1_{\{m\text{'th percentile} < YFR_t \leq (100-m)\text{'th percentile}\}} + \\ & \lambda^{High} \times 1_{\{YFR_t > (100-m)\text{'th percentile}\}} + \epsilon_{t+12} \end{aligned}$$

for $n \in \{15, 20, 25, 30, 35\}$ and $m \in \{20, 25, 30, 35\}$. Table A2 presents the coefficient estimates and t-statistics for the different specifications for both corporate bonds (Panel A) and equities (Panel B). For both asset classes and all specifications, we see an inversion of the risk-return relationship when YFR_t is low. The inversion is statistically significant across all specifications, except when applying the loosest portfolio criteria (n=35) to the bond market portfolios. As expected, raising the criteria for portfolio inclusion (i.e. lowering n) decreases the β^{low} estimates, and increases β^{high} estimates, as the differences in risk between the high-risk and the low-risk portfolio increases. Likewise, as we sharpen the criteria for what constitutes periods of high and low YFR_t, the coefficient estimates increase (in absolute sense) as the indicator variables capture periods of more pronounced sentiment.

In addition to the robustness tests above, I estimate the potential influence of finite sample bias using the block-bootstrap methodology described in Section 4.1.1. Table A3 presents estimates of p-values and biases in coefficient estimates from the bootstrap procedure. We see

that finite sample biases do not seem to be driving the risk-return inversion. For example, the bootstrap bias estimate of my baseline coefficient estimate λ^{Low} for corporate bond returns is -0.06% compared to a coefficient estimate of -0.84%. Similarly, for equity returns the bootstrap bias estimate of λ^{Low} is -0.61% relative to a coefficient estimate of -7.78% in my original regression. Further, the results of the bootstrap-t procedure shows us that the statistical significance remains.

4.3 Predicting Aggregate Bond Market Returns

Sentiment should predict not only the returns to credit risk in the cross-section as documented above, but also the time-series as measured by returns to the aggregate bond market. To test this hypothesis, I measure the h-month excess return of the aggregate bond market as the difference between the average h-month return of all bonds in my panel (including non-investment grade bonds) and the h-month risk-free Treasury yield. I regress the excess return of the bond market on YFR_t:

$$r^{mkt}_{t+h} - y^{f,h}_t = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \delta^T Z_t + \epsilon_{t+h} \tag{9}$$

where r^{mkt}_{t+h} is the return on the aggregate bond market from time t to $t+h$ and $y^{f,h}_t$ is the h-month Treasury yield at time t. The yield-for-risk parameter, YFR_t, is normalized by its standard deviation, and X_{t+h} is a vector of control variables which contains the change in the level of the 10-year Treasury yield, and the change in the slope of the Treasury yield curve as in regression (5). The vector Z_t contains a series of alternative measures of bond market sentiment; the Excess Bond Premium (Gilchrist and Zakrajšek, 2012), the High Yield Share (Greenwood and Hanson, 2013), the CBOE VIX, and the BAA Spread.

Table 5 presents the results. Panel A shows that yield-for-risk is a strong predictor of aggregate excess bond market returns with a one standard deviation increase in YFR_t increasing excess aggregate bond market returns by .23% over the following month, 1.29% over the following 6 months, and 2.07% over the following 12 months. Controlling for contemporaneous changes in Treasury yields does not alter the predictive power of YFR_t, indicating that it is indeed fluctuations in the price of credit risk that YFR_t predicts.

I again test the strength and novelty of YFR_t as a predictive variable by including the known measures of sentiment listed in the vector Z_t in the predictive regression. Table 5, Panel B presents the results at the 12-month prediction horizon, and we see that YFR_t maintains its predictive power despite the inclusion of alternative predictors. I control for changes in the term structure of risk-free rates by including changes in the level and slope

of Treasury yields in the regression as above.[17]

The strong predictability of bond market returns, raises the question if the return on the equity market is also predicted by YFR_t. According to the model of Section 5, the determinants of the returns to the aggregate bond market and the aggregate equity market should be the same, and we therefore expect to see the same predictive power for aggregate equity market returns as for aggregate bond market returns. I rerun regression (9) with the excess aggregate equity market return as the dependent variable, and while there is a positive relationship between YFR_t and future excess equity market returns, the relationship is not statistically significant.[18]

4.4 Predicting Debt Issuance

It is well-known that firms adjust their capital structure in response to the valuations of their assets (Baker and Wurgler, 2000; Ma, 2019). To see how firm behavior relates to YFR_t, I run a panel regression of net debt issuance on YFR_t using quarterly book data from Compustat. Table 6 presents the results of the forecasting regression:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \delta^T Z_{it} + \epsilon_{it+3} \tag{10}$$

where $Issuance_{it+3}$ is the net debt issuance measured as the difference between long-term debt issuance (`dltis`) and long-term debt reduction (`dltr`) over the quarter from t to $t+3$. Yield-for-risk, YFR_t, is the parameter estimate from equation (1) normalized by its standard deviation, and Z_{it} is a vector of control variables which contains measures of balance sheet strength, the 10-year US Treasury yield as well as 4 quarterly lags of the dependent variable. I include lags of the dependent variable to control for trends in firm debt issuances, as well as potential omitted variables, while the 10-year Treasury yield is included to control for the level of interest rates broadly. To control for balance sheet strength, I include the firm's cash holdings and short-term investments (`cheq`), as well as net income (`niq`) and earnings (`ebitda`) over the previous quarter. All balance sheet variables are normalized by the lag total assets of the firm (`atq`). I include all non-financial firms in Compustat and not just the firms present in my bond panel.[19]

[17] In untabulated tests, I rerun the analysis using the adjusted bond returns described in the robustness tests of Section 4.1.1 with no consequence to the results.

[18] I obtain the value-weighted equity market return of all US firms listed on NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 from Ken French's website: mba.tuck.dartmouth.edu/pages/faculty/ken.french, and use this as my measure of the aggregate equity market return.

[19] My results do not change materially, if I restrict my sample to include only firms with bonds in my panel, though the statistical significance is somewhat dampened due to the lower number of observations.

Table 6 shows that a one standard deviation decrease in YFR_t is associated with an average increase in debt issuance of 0.31% over the following quarter measured as a percentage of firm assets. From Table 6, Column 2 we see that YFR_t retains its predictive power when including the control variables, though the parameter estimate falls a bit to -0.29%. As an additional robustness test, Column 3 of Table 6 presents the results of the regression model with firm fixed effects as an alternative to the inclusion of lagged dependent variables. The firm fixed effects specification has the advantage that it controls for any time-invariant, firm-specific omitted variable which could influence my result due the changing composition of my panel. We see that the change in specification causes only a small decrease in the predictive power of YFR_t.

Compustat only reports long-term debt issuance (and reduction) beginning in 1984 and so the prediction exercise using net debt issuance as the dependent variable does not span the full time-series for which YFR_t is available. I therefore rerun the forecasting regression in equation (10), but replace net debt issuance with the change in total liabilities as the dependent variable. I measure total liabilities as the difference between a firm's total assets (`atq`) and book equity.[20] The change in total liabilities is a broader measure of a firm's leverage than net debt issuance as it includes all firm liabilities and not just long-term debt. Column 4 of Table 6 presents the results of regression (10) with the change in total liabilities as dependent variable, and shows us that a one standard deviation decrease in YFR_t is an even stronger predictor of the change in total liabilities ($\beta = -0.47\%$) than of the net debt issuance. Overall, the results tell us that periods of low YFR_t are periods where firms increase their leverage by increasing both their long-term debt issuance and by increasing other liabilities.

The unbalanced nature of my panel may mean my results are driven primarily by the dates with relatively more observations. To mitigate this concern, I collapse my panel into a single time-series by measuring the average net debt issuance, and the average change in total liabilities, at each date, and regress these averages on YFR_t, the 1-year Treasury yield and four quarterly lags of the dependent variable. Columns 5 and 6 of Table 6 presents the results. I find that YFR_t still predicts net debt issuance and change in total liabilities in the collapsed time-series setting.

Having documented that firms on average increase their debt issuance when YFR_t is low, I now test whether it is the riskiest firms who are most sensitive to sentiment. I measure the

As with the bond panel, I restrict the sample to only include firms with a market capitalization above \$50 m. in 2016 inflation-adjusted terms.

[20] Book equity is defined as in Fama and French (1993) as stockholders' equity (`seqq`) plus deferred taxes and investment tax credit (`txditcq`) minus preferred stock (`pstkq`). Deferred taxes, investment tax credit and preferred stock are accounted for when provided and otherwise set to zero.

relative riskiness of each firm i at each date t as the fraction of firms which are safer that firm i at time t:

$$Risk_{it} = \frac{1}{k_t - 1} \sum_{j=1}^{k_t} 1_{\{\widetilde{DD}_{jt} > \widetilde{DD}_{it}\}} \tag{11}$$

Here, k_t is the number of firms in the panel at time t, and $1_{\{\widetilde{DD}_{jt} > \widetilde{DD}_{it}\}}$ is an indicator variable that switches on if firm j has a higher distance-to-default than firm i at time j. The construction of the variable ensures that the riskiest firm at a given point in time has $Risk_{it} = 1$ while the safest firm has $Risk_{it} = 0$. Table 7 presents the results of the regression:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \chi \times Risk_{it} + \xi \times YFR_t \times Risk_{it} + \delta^T Z_{it} + \epsilon_{it+3} \tag{12}$$

where Z_{it} includes the same control variables as in regression specification (10). Table 7 shows that the main effect of the risk variable is between -0.7% and -1.1% depending on the specification. This means the riskiest firm in the cross section on average issues less debt as a percentage of total assets than the safest. This is not surprising as safe firms have a higher debt capacity, and thus can issue more debt at lower rates. The more interesting part of the analysis is the negative interaction effect between the cross-sectional risk measure and YFR_t. For example, Column 1 of Table 7 shows that the main effect of YFR_t is -0.20%, while the interaction effect between YFR_t and the risk percentile is -0.23%, meaning the riskiest firm in the cross-section is more than twice as sensitive to YFR_t than the safest firm in the cross-section. Columns 2 and 3 show that the result is robust to the inclusion of lagged dependent variables and controls for balance sheet strength. Further, the result holds when changing the dependent variable to changes in total liabilities as shown in Column 4.

The periods of low YFR_t are of special interest in my analysis as they are periods of potential risk neglect. I take a closer look at these periods by testing if it is the riskiest firms that increase their debt, and by how much, in periods of low YFR_t, as we would expect given the results in Table 7. To do so, I estimate the regression:

$$\begin{aligned} Issuance_{it+3} = &\sum_{k=1}^{5} \chi_k 1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}} \\ &+ \sum_{k=1}^{5} \xi_k \left(1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}} \times 1_{\{\text{Low } YFR_t\}} \right) + \delta^T Z_{it} + \epsilon_{it+3} \end{aligned} \tag{13}$$

where Z_{it} contains the same control variables as in regression (10), i.e., the 10-year US Treasury yield, four lags of the dependent variable, as well as the firm's cash holdings and

short-term investments (`cheq`), net income (`niq`), and earnings (`ebitda`) over the previous quarter, normalized by the lag total assets of the firm (`atq`). $1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}}$ is an indicator variable that switches on if $\widetilde{DD}_{it}$ is in the k'th quintile at time t. For example, for the indicator variable $1_{\{\widetilde{DD}_{it} \text{ in } 1^{st} \text{ Quintile}\}}$ takes the value of one if the firm i is among the 20% riskiest firms at time t. The indicator variable $1_{\{YFR_t<25^{\text{th}} \text{ pct.}\}}$ switches on if YFR_t is below its 25^{th} percentile. The average issuance of firms in the k'th risk quintile when YFR_t is high (i.e. not in its lowest quartile), is thus measured by χ_k, while ξ_k measures the difference in debt issuance by firms in the k'th risk quintile between periods where YFR_t is in its lowest quartile, and periods when it is not. For example, χ_1 measures the average net debt issuance by 20% riskiest firms when YFR_t is the top 75% of its full sample distribution, and ξ_1 measures the additional debt issuance by the riskiest firms when YFR_t enters its lowest quartile. This means that $\chi_1 + \xi_1$ measures the total net debt issuance of the riskiest firms when YFR_t is in its lowest quartile. I dub ξ_k the additional net debt issuance. Figure 4 Panel A presents a plot of the average debt issuance (χ_k) of firms by risk group. Consistent with Table 7, it is the safest firms which issue most debt when YFR_t is high. Figure 4 Panel B plots the additional net debt issuance (ξ_k) by firms in each of the risk groups when YFR_t is in its lowest quartile, and shows that it is the riskiest firms which increase their debt issuance when YFR_t is low. In contrast, the safest firms do not adjust their issuance between periods of low YFR_t and high YFR_t. The increase in debt issuance by the riskiest firms is substantial relative to their issuance outside the period of low YFR_t, where their net debt issuance is not significantly different from 0. Specifically, the riskiest 20% of firms increase their net debt issuance by a statistically significant 0.66% of total assets when YFR_t is in its lowest quartile relative to other periods. In contrast, the safest 20% of firm do not change their issuance between periods of low YFR_t and high YFR_t. The coefficients presented in Figure 4 are estimated controlling for the level of the 10-year Treasury yield, four lags of the dependent variable, and the strength of the firms' balance sheets. Table A4 in the Appendix presents the table version of the regression illustrated in Figure 4 in column 5, and further shows that the result is not sensitive to the choice of control variables.

The result suggests that credit cycles may be driven, in large part, by the net debt issuance of the riskiest firms in the economy, who take advantage of the low compensation for risk required by investors. The result is consistent with Greenwood and Hanson (2013) who show that the composition of debt issuers is a strong predictor of returns to the aggregate bond market. In Table A5 of the appendix, I further show that low YFR_t is associated with an increase in net equity purchases and a decrease in cash holdings by the largest firms in the economy. Further, all firms, small and large, increase their capital expenditure when YFR_t is low. The results suggests that low YFR_t is associated with both an increase in investments,

and with cross-market arbitrage (Ma, 2019) as firms substitute debt for equity.

5 A Model of Extrapolative beliefs and Credit Risk Neglect

This section develops a simple equilibrium model with extrapolative beliefs to interpret the empirical evidence in Sections 3–4. The model formalizes credit risk neglect: following good news, investors underweight downside default risk when pricing corporate claims, which compresses YFR_t and can invert the risk–return relationship in both bonds and equities.

5.1 Model setup

I consider an economy with an infinite number of firms financed by debt and equity. The economy has two periods, $t \in \{0, T\}$. At time 0, a representative investor maximizes the expected utility of his consumption by constructing a portfolio from the assets issued by the firms. At time T, the value of the firms is returned to the investor through the bonds and stocks issued. The investor's portfolio choice determine equilibrium asset prices and reflect both the investor's preferences and beliefs.

Firms and Assets. The (log) payoff of firm i's underlying assets, V_i, is given as the sum of three variables:

$$\log V_i = \delta + \epsilon_C + \epsilon_i. \tag{14}$$

Here, δ reflects news about the economy and is a parameter common to all firms, ϵ_C is a common shock affecting all firms equally, and ϵ_i is an idiosyncratic shock specific to firm i. The common shock and the idiosyncratic shocks are all independent, normally distributed with mean zero and variances of σ_C^2 and σ_I^2, respectively. Further, all idiosyncratic shocks in the economy are mutually independent. The news parameter δ is perfectly observable to the investor and determines the expected (log) payoff of the firms. A positive delta reflects good news about the economy and all firms become more profitable, and vice versa for a negative delta. We can think of δ as news about GDP growth, unemployment, or other macroeconomic variables, which influence the earnings potential of all firms in the economy.

Each firm has a supply of shares normalized to one and a supply of bonds expiring at time T, which is also normalized to one. The face value of the bonds issued by firm i is denoted by K_i, and is the key feature which distinguishes firm i from the other firms in the

economy at time 0. The time-T payoffs of firm i's bonds, D_i, and stocks, E_i, are:

$$D_i = \min\{V_i, K_i\} \tag{15}$$

$$E_i = \max\{V_i - K_i, 0\} \tag{16}$$

In case of default, $V_i < K_i$, the equity holders are wiped out, and the remaining value of the firm falls to the bond holders. If a firm does not default, bond holders are paid in full, and equity investors receive the residual claim on the firm's underlying assets.

The total market payoff $V_{Mkt.}$ is the sum of the payoffs of the assets issued by the firms in the economy:

$$V_{Mkt.} = \int_{\mathcal{A}} V_i d\mu_i = \exp\{\delta + \frac{1}{2}\sigma_I^2 + \epsilon_C\} \tag{17}$$

where $\mathcal{A}$ denotes the set of firms in the economy which have a mass of one, and μ is the measure which assigns weights to the firms.[21] Finally, a risk-free asset which promises a payoff of one at time T is available in zero net supply.

Representative Investor. A representative investor seeks to maximize his expected utility of consumption over the model's two periods by choosing the amount of risk-free asset, π^{rf}, as well as the number of bonds, π_i^D, and stocks, π_i^E, from each firm i to include in his portfolio. The investor's utility function, u, formalizes his constant relative risk aversion:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{18}$$

where γ is the relative risk aversion parameter. The investor is initially endowed with all assets in the economy, as well as some amount of non-financial wealth W_0. At time 0, the investors consumption, C_0, thus equals his initial endowment (non-financial wealth plus assets) minus the cost of his portfolio. At time T, the investors consumption, C_T, equals the payoff of his portfolio. The investor's maximization problem is:

$$\max_{\pi_i^D, \pi_i^E, \pi^{rf}} \quad u(C_0) + E^\theta[u(C_T)]$$

[21] Applying the law of large numbers to get to the aggregate market payoff requires a particular structure on the set of firms in the economy, $\mathcal{A}$. I take the structure as given here and refer to Constantinides and Duffie (1996) p. 226-227 for a technical discussion.

$$\text{s.t.} \qquad C_0 = W_0 - \int_{\mathcal{A}} (\pi_i^E - 1) P_i^E d\mu_i - \int_{\mathcal{A}} (\pi_i^D - 1) P_i^D d\mu_i - \pi^{rf} \exp\{-y^f\} \tag{19}$$
$$C_T = \int_{\mathcal{A}} \pi_i^E E_i + d\mu_i + \int_{\mathcal{A}} \pi_i^D D_i d\mu_i + \pi^{rf}$$

where P_i^D denotes the price of firm i's bonds, P_i^E denotes the price of firm i's equity, and y^f denotes the risk-free (log) bond yield.[22]

The investor's expectation about the assets' future payoffs is based on the observed news about the economy δ, which the investor a priori assumes will be 0,. The superscript θ in the expectation in equation (19) indicates that the investor has diagnostic expectations (Bordalo, Gennaioli, and Shleifer, 2018), which is a formalization of the Kahneman and Tversky (1972) representativeness heuristic. Diagnostic expectations depart from rational expectations by overweighing states of the world that are *representative* of the news about the economy, i.e. states of the world that have become more likely given the observed news δ relative to the investors prior ($\delta = 0$), and underweighing other states. Formally, under diagnostic expectations, the investor evaluates expectations using a distorted density function $f^\theta(V_i|\delta)$, which combines the true density function of a firm's payoffs, $f(V_i|\delta)$, with the representativeness, $\frac{f(V_i|\delta)}{f(V_i|\delta=0)}$, of the firm's payoffs:

$$f^\theta(V_i|\delta) = f(V_i|\delta) \left(\frac{f(V_i|\delta)}{f(V_i|\delta = 0)} \right)^\theta \times C \tag{20}$$

Here, $\theta \geq 0$ governs how distorted the investor's beliefs are, and $C = \exp\left\{ \frac{-\delta^2 \theta(1+\theta)}{2\sigma^2} \right\}$ is a constant that ensures that f^θ integrates to one. I use the superscript θ throughout the paper to indicate densities and expectations formed under the diagnostic measure.

Extrapolation occurs as the investor observes news δ, and overestimates how good or bad the news actually is by assigning too high probabilities to states of the world that become objectively more likely given the news $\frac{f(V_i|\delta)}{f(V_i|\delta=0)} > 1$, i.e., states which are representative, and too low probabilities to states of the world which become objectively less likely $\frac{f(V_i|\delta)}{f(V_i|\delta=0)} < 1$.[23] Risk neglect occurs following good news as the investor underestimates the probability of low realizations of firm value V_i, which have become less likely given the good news.

A convenient feature of coupling diagnostic expectations with lognormally distributed payoffs is that investors still perceive a firm's payoff as being lognormally distributed, but

[22] To limit notation, I assume the investor has no preference regarding the timing of his consumption.

[23] To be exact, it is the states of the world which are *sufficiently* representative, $\left(\frac{f(V_i|\delta)}{f(V_i|\delta=0)} \right)^\theta \times C > 1$, that are overweighted under diagnostic expectations. This small correction stems from the normalization constant C.

with a biased location parameter, as I show next.[24]

Lemma 1. *An investor with diagnostic expectations perceives the underlying value of the firm as being lognormally distributed with a biased location parameter equal to* $\delta(1+\theta)$*, and shape parameter equal to the true shape parameter:* $\sigma_V = \sqrt{\sigma_I^2 + \sigma_C^2}$.

Equilibrium. In equilibrium the representative investor's demand for stocks and bonds equals the supply, $\pi_i^E = \pi_i^D = 1$, for all i, and the demand for the risk-free asset equals zero, $\pi^{rf} = 0$. As a consequence, the investor consumes his full initial non-financial wealth endowment at time 0, $C_0 = W_0$, and the aggregate payoff of the market at time T, $C_T = V_{Mkt.}$. Without loss of generality, I normalize the initial wealth of the investor to 1.

5.2 Theoretical results

This section presents the key theoretical results regarding asset prices and expected returns in the economy. By combining the equilibrium conditions with the investor's first-order conditions, I derive expressions for expected returns on the firms' total assets, as well as their debt and equity components. I further analyze the implications for credit spreads, the risk-return relationship, and derive testable predictions. Proofs and additional results are relegated to the Appendix.

Expected Return on Firm Assets. I begin by analyzing the expected return on a firm's total assets. Let $R_i = \frac{V_i}{P_i^V}$ be the gross return on firm i's total assets, where P_i^V is the time 0 price of firm i's assets, and V_i is the payoff of firm i's assets. The following proposition characterizes the rational expected excess return on these assets.

Proposition 1 (**Expected Return on Firm**). *The (log) expected excess return on firm* i*'s assets is:*

$$\log E[R_i] - y^f = \gamma\sigma_C^2 - \delta\theta$$

where $y^f = \gamma[\delta(1+\theta) + \frac{1}{2}\sigma_I^2] - \frac{1}{2}\gamma^2\sigma_C^2$ *is the equilibrium risk-free (log) bond yield.*

As stated in Proposition 1, the expected excess return on a firm's total assets are determined by two key components: the standard risk premium ($\gamma\sigma_C^2$) and a belief-induced bias ($-\delta\theta$). The risk premium, $\gamma\sigma_C^2$, reflects the investor's required compensation for bearing market risk and is what the investor expects to receive. The bias, $-\delta\theta$, occurs as the investor extrapolates the news, δ, leading him to misprice to value of the company and changing the

[24] Lemma 1 echoes findings of Maxted (2024) and Bordalo, Gennaioli, Shleifer, and Terry (2021) who study real business cycle models with diagnostic expectations.

true expected return on the firm's total assets. In particular, if the investor's beliefs are sufficiently biased, $\theta > \frac{\gamma\sigma_C^2}{\delta}$, and he receives good news $\delta > 0$, the expected excess return of the firm's underlying assets becomes negative. Note that the expected excess return on a firm's total assets is identical across all firms as they only differ in their capital structure (Modigliani and Miller, 1958).

Credit Spreads and Expected Returns on Bonds and Stocks. Having established the expected return on a firm's total assets, I now decompose this return into the expected returns on the firm's bonds and stocks. These returns are influenced by the same factors determining the return on total assets, but are further shaped by the firm's capital structure and associated credit risk. To quantify credit risk, I utilize distance-to-default (DD_i), defined as:

$$DD_i = \frac{\delta - \log(K_i)}{\sigma_V} \tag{21}$$

where $\sigma_V = \sqrt{\sigma_I^2 + \sigma_C^2}$ is the volatility of the firms (log) assets as before, and $\delta - \log(K_i)$ is the distance between the firm's expected (log) payoff, δ, and its (log) default barrier, $\log K_i$. Distance-to-default essentially captures how many standard deviations away a firm's expected asset value is from its default point.

To further analyze bond and stock returns, it is convenient to first introduce the credit spread (cs_i) for firm i's bonds, defined as the difference between the bond's (log) yield (y_i) and the risk-free (log) bond yield (y^f). The following proposition provides an expression for this credit spread:

Proposition 2 (**Credit Spread**). *The (log) credit spread on firm i's bond is:*

$$cs_i = -\log\left(\frac{P_i^V}{\exp\{-y^f\}K_i}\Phi\left(-DD_i - \sigma_V + \frac{\gamma\sigma_C^2 - \theta\delta}{\sigma_V}\right) + \Phi\left(DD_i - \frac{\gamma\sigma_C^2 - \theta\delta}{\sigma_V}\right)\right) \tag{22}$$

where Φ is the cumulative density function of a standard normal distribution.

Proposition 2 reveals that a firm's credit spread is determined by two key factors: (1) the firm's credit risk, measured by DD_i; (2) expected excess return on firm i's assets, $\gamma\sigma_C^2 - \delta\theta$. Building upon the determinants of credit spreads and the expected return on firm assets, the expected returns on a firm's bonds ($R_i^D = \frac{D_i}{P_i^D}$) and stocks ($R_i^E = \frac{E_i}{P_i^E}$) follow directly.[25]

Proposition 3 (**Expected Returns on Assets**).

[25]Consistent with earlier notation, I let P_i^D and P_i^E denote the prices of firm i's bonds and stocks, respectively.

1. *The (log) expected excess return on firm i's bond is the difference between the log credit spread and the log expected loss on the bond:*

$$\log E[R_i^D] - y^f = cs_i - el_i$$

where cs_i is the credit spread of the firm's bonds and $el_i = -\log(E[1_{\{V_i>K_i\}}+1_{\{V_i<K_i\}}\frac{V_i}{K_i}])$ is the (log) expected loss on the bonds.

2. *The (log) expected excess return on firm i's equity is the (log) expected excess return on firm i's assets amplified by the firm's leverage:*

$$\log E[R_i^E] - y^f = \log E[R_i] - y^f + \log\left(1 + L_i\left(\frac{E[R_i] - E[R_i^D]}{E[R_i]}\right)\right)$$

where $L_i = \frac{P_i^D}{P_i^E}$ is the leverage of the firm.[26]

Proposition 3 highlights that the expected returns on both bonds and stocks are fundamentally linked to the expected excess return on the firm's total assets ($\log E[R_i] - y^f = \gamma\sigma_C^2 - \delta\theta$). Specifically, higher expected excess returns on firm assets generally translate to higher expected returns on both bonds and stocks. However, the relationship with credit risk, embedded in the firm's capital structure, is more nuanced. When the expected excess return on firm assets is positive ($\gamma\sigma_C^2 - \delta\theta > 0$), a higher credit risk (lower distance-to-default) is associated with higher expected returns on both bonds and stocks, reflecting a standard positive risk-return relationship. Conversely, the situation changes when the expected excess return on firm assets becomes negative, as I discuss next

Risk-Return Inversion. The model predicts a that extrapolative beliefs can lead to a negative expected excess return on the firm's total assets. In the cross section of bonds and stocks, this inverts the risk-return relationship as formalized in the following proposition:

Proposition 4 (**Risk-Return Inversion**). *The relationship between credit risk and expected return inverts when news is good, and the investor's beliefs are sufficiently biased: $\gamma\sigma_C^2 - \delta\theta < 0$:*

$$\frac{\partial}{\partial DD_i} E[R_i^E] > 0$$
$$\frac{\partial}{\partial DD_i} E[R_i^D] > 0$$

As Proposition 4 indicates, when good news amplifies investor bias to the extent that the

[26] Proposition 3.2 is a restatement of Modigliani and Miller (1958) Proposition 2.

return on the firm's total assets becomes negative ($\gamma\sigma_C^2 - \delta\theta < 0$), the risk-return relationship inverts for both bonds and stocks. In this scenario, increased credit risk (proxied by higher K_i and lower DD_i) leads to *lower* expected returns. This result arises because investors, swayed by extrapolative beliefs, underestimate the probability of bad realizations of the firm's total payoff V_i, which means that credit spreads rise slower than expected losses in the cross section as the firm's capital structure becomes riskier. Similarly, the firm's equity is still a levered bet on the firm's total assets, but the premium earned on these assets is negative.

Figure 5 - Panel A illustrates the relationship between risk in the firm's capital structure and the expected returns on a firm's assets, both in a "normal" economy where the risk-return relationship is positive, and an overheated economy where beliefs are sufficiently distorted to invert the risk-return relationship ($\gamma\sigma_C^2 - \delta\theta < 0$). The risk in the firm's capital structure is measured as the negative of the firm's DD_i, and we see that in the "normal" economy the expected returns on both bonds and stocks increase as the firm becomes riskier, while the relationship inverts when beliefs of sufficiently distorted. As mentioned, the Modigliani and Miller (1958) propositions hold in both cases, as it is the fundamental value of the firm, which the investor gets wrong, not the value of one particular asset. It is because investors extrapolate the fundamental value of the firm that the risk-return relationship to invert simultaneously in the bond and stock market.

Yield-for-Risk. True expected returns are not directly observable.[27] However, credit spreads are observable market quantities determined by the same factors that determine the expected returns on a firm's bonds and stocks: the return on the firm's total assets ($\gamma\sigma_C^2 - \delta\theta$) and credit risk ($DD_i$). Therefore we can assess the overall risk-return sentiment in the market by measuring the cross-sectional relationship between credit spreads and credit risk. To do so, I define Yield-for-Risk (YFR):

Definition 1 (**Yield-for-risk**). *Yield-for-risk is the average derivative of the credit spread wrt. distance-to-default:*

$$YFR = -\int_{\mathcal{A}} \frac{\partial cs_i}{\partial DD_i} d\mu_i > 0$$

Yield-for-Risk (YFR) provides a measure of the average market compensation for bearing credit risk in the cross section. A higher YFR suggests that investors, on average, demand a larger increase in credit spreads for each unit increase in credit risk. Conversely, a lower

[27] Note that even if survey data was available for firm level expected returns, or expected returns at the bond or stock level, these would reflect the investors' required rate of return, which due to biased expectations might not align with the true rate of return.

YFR indicates a weaker compensation for credit risk.[28] In fact, YFR provides an upper bound on the market's perception of how much expected losses on bonds increase on average when a firm moves one standard deviation closer to default. Even if the investor is risk neutral, credit spreads must at least make up for differences in expected losses. Figure 5 - Panel B illustrates how the sensitivity of credit spreads to credit risk decreases as the market risk premium ($\gamma\sigma_C^2 - \delta\theta$) decreases. Thus, YFR serves as a valuable proxy for market sentiment and the risk-return relationship. Its advantage lies in its direct interpretability, its utilization of cross-sectional information from all firms, and its empirical tractability, as will be discussed in Section 3.

Testable Predictions. The theoretical framework outlined above leads to the following testable predictions:

1. Yield-for-risk predicts the expected return to credit risk in both the cross-section of bonds and stocks, as measured by the return spreads of risky bonds over safe bonds, and risky stocks over safe stocks.
2. Similarly, yield-for-risk predicts the average returns to both the bond and the stock market.
3. Finally, if beliefs are extrapolative, $\theta > \frac{\gamma\sigma_C^2}{\delta}$, a low yield-for-risk coincides with an inversion of the risk-return relationship in both the bond and the stock market.

6 Conclusion

I consider an equilibrium asset pricing model of corporate bonds and stocks, which includes both rational risk aversion and extrapolative beliefs embedded via diagnostic expectations. I test the predictions generated by the model's two mechanisms by introducing a new measure of credit market sentiment named yield-for-risk. Using yield-for-risk, I document periods of almost complete disconnect between credit spreads and risk in the cross-section of bonds, and find that these periods are associated with low past defaults, loose lending standards and high past returns on both the bond and the stock market. I further document that periods of low yield-for-risk coincide with an inversion in the risk-return relationship in both the bond market and the stock market. That is, when yield-for-risk is low, the expected returns of high-risk bonds and stocks are significantly lower than the expected returns of

[28] You can get a sense of YFR's dependence on the market risk premium and credit risk from the first-order derivative directly:

$$-\frac{\partial cs_i}{\partial DD_i} = \sigma_V \frac{P_i^V}{P_i^D} \Phi(-DD_i + \frac{\gamma\sigma_C^2 - \delta\theta}{\sigma_V} + \sigma_V) > 0. \tag{23}$$

low-risk bonds and stocks. I further find that yield-for-risk is a strong predictor of the aggregate returns to the bond market, as well as the net debt issuance. In particular, it is the net debt issuance by the riskiest firms, which is sensitive to the level of yield-for-risk.

The evidence is consistent with the model's predictions, that investors, at times, overestimate the fundamental value of risky firms relative to safe firms, and overpay for the riskiest firms' bonds and stocks. The findings indicate that extrapolative beliefs are a central driver of credit prices and credit growth, and support the boom-bust hypothesis of credit cycles proposed by Kindleberger (1978) and Minsky (1977). As such, yield-for-risk provides a novel and useful tool for policy makers to assess the level of optimism in the bond market. As yield-for-risk is derived from price and book data, a natural extension of this paper would be to combine yield-for-risk with measures of economic fragility, such as credit growth, and see if the combination increases the predictive power of yield-for-risk on both returns and economic outcomes. I leave this question for future research.

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Figure 2. Yield-for-Risk.

This figure presents the time-variation in my measure of credit market sentiment, yield-for-risk (YFR_t). YFR_t is estimated from a cross-sectional regression of the time-t credit spread, $y_{ijt} - y^f_{jt}$, of the bond j issued by firm i on firm i's distance-to-default, $\widetilde{DD}_{it}$, at time t:

$$y_{ijt} - y^f_{jt} = \alpha_t + YFR_t \times (-\widetilde{DD}_{it}) + \delta^T_t Z_{ijt} + \epsilon_{ijt}$$

where Z_{ijt} contains the control variables bond duration, bond age and firm size (all in logs). The credit spread of bond j is defined as the yield of bond j minus the yield of a US Treasury bond with duration equal to that of bond j, and the firm's distance-to-default is calculated following the methodology of Bharath and Shumway (2008). The shaded areas mark NBER economic recessions.

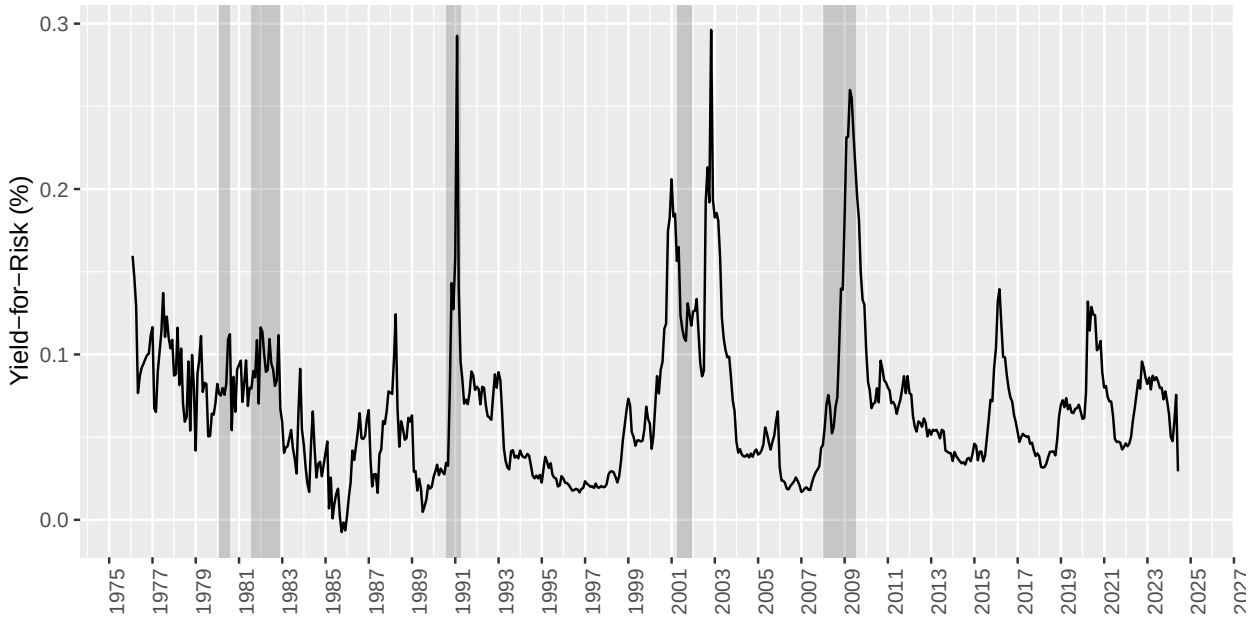


Figure 3. Cross-section of Credit Spreads and Risk.

This figure presents a scatter plot of credit spreads and the distance-to-default on, respectively, May 31st, 2007 and March 31st, 2009. The dashed lines illustrate the fit of credit spreads regressed on distance-to-default at each date:

$$y_{ijt} - y^f_{jt} = a - b \times \widetilde{DD}_{it} + e_{it}$$

where $y_{ijt} - y^f_{jt}$ is the credit spread of bond j at time t issued by firm i over the yield of a US Treasury bond with duration equal to that of of bond j, $\widetilde{DD}_{it}$ is the firm's distance-to-default. The figure shows a low estimate of b (i.e. a low yield-for-risk) in May 2007 immediately prior to the Global Financial Crisis (GFC), and a high estimate of b (i.e. a high yield-for-risk) during the GFC in March 2009.

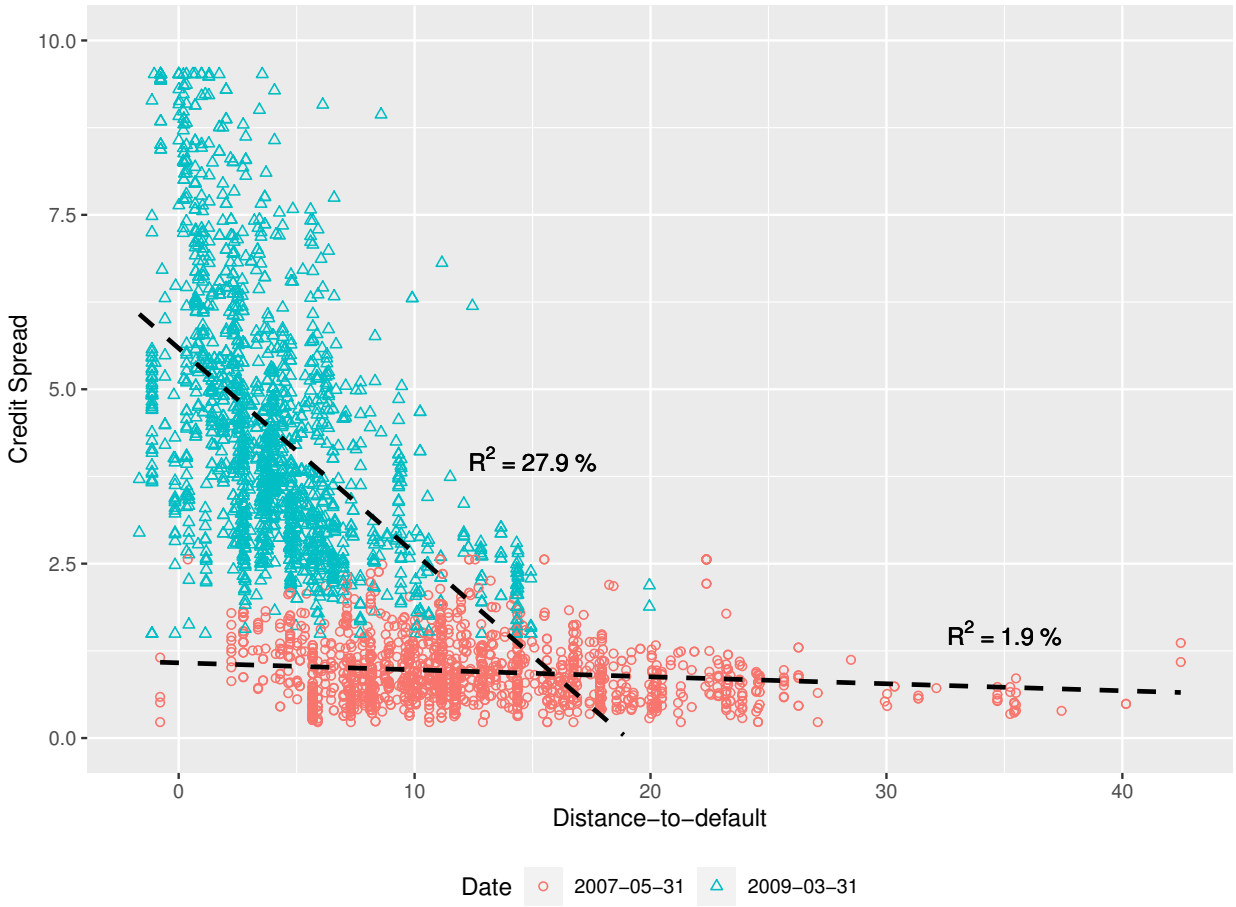


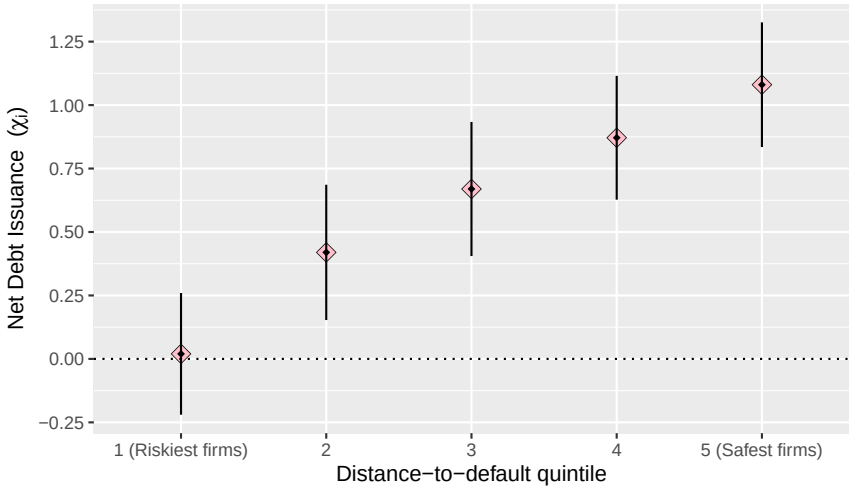
Figure 4. Excess Debt Issuance.

Panel A presents the average quarterly net debt issuance (χ_k) when yield-for-risk (YFR_t) is high (above its 25$^{\text{th}}$ percentile), and Panel B presents the additional average quarterly net debt issuance (ξ_k) when yield-for-risk is low (below its 25$^{\text{th}}$ percentile). Firms are split into five groups from the riskiest to the safest, depending on their distance-to-default. Average and additional issuance is measured for each group from the regression:

$$Issuance_{it+3} = \sum_{k=1}^{5} (\chi_k + \xi_k \times 1_{\{\text{Low } YFR_t\}}) \times 1_{\{\widetilde{DD}_{it} \text{ in } k\text{'th Quintile}\}} + \delta^T Z_{it} + \epsilon_{it+3}$$

where Z_{it} contains control variables, consisting of the ten-year Treasury bill rate, four lags of the dependent variable, and controls for the strength of the firms balance sheet (cash, net income and EBITDA). The bars illustrate the 95% confidence interval calculated with Driscoll and Kraay (1998) standard errors using 4 lags and Kiefer and Vogelsang (2005) "fixed-b" asymptotics. The figure shows that high-risk firms increase their debt issuance when yield-for-risk is low, while low-risk firms do not change their issuance.

Panel A: *Average net debt issuance: dates with high YFR_t*



Panel B: *Additional net debt issuance: dates with low YFR_t*

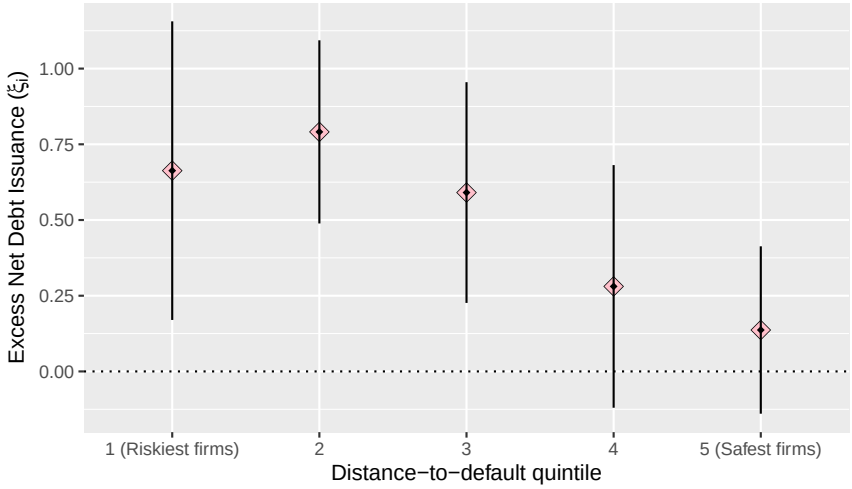
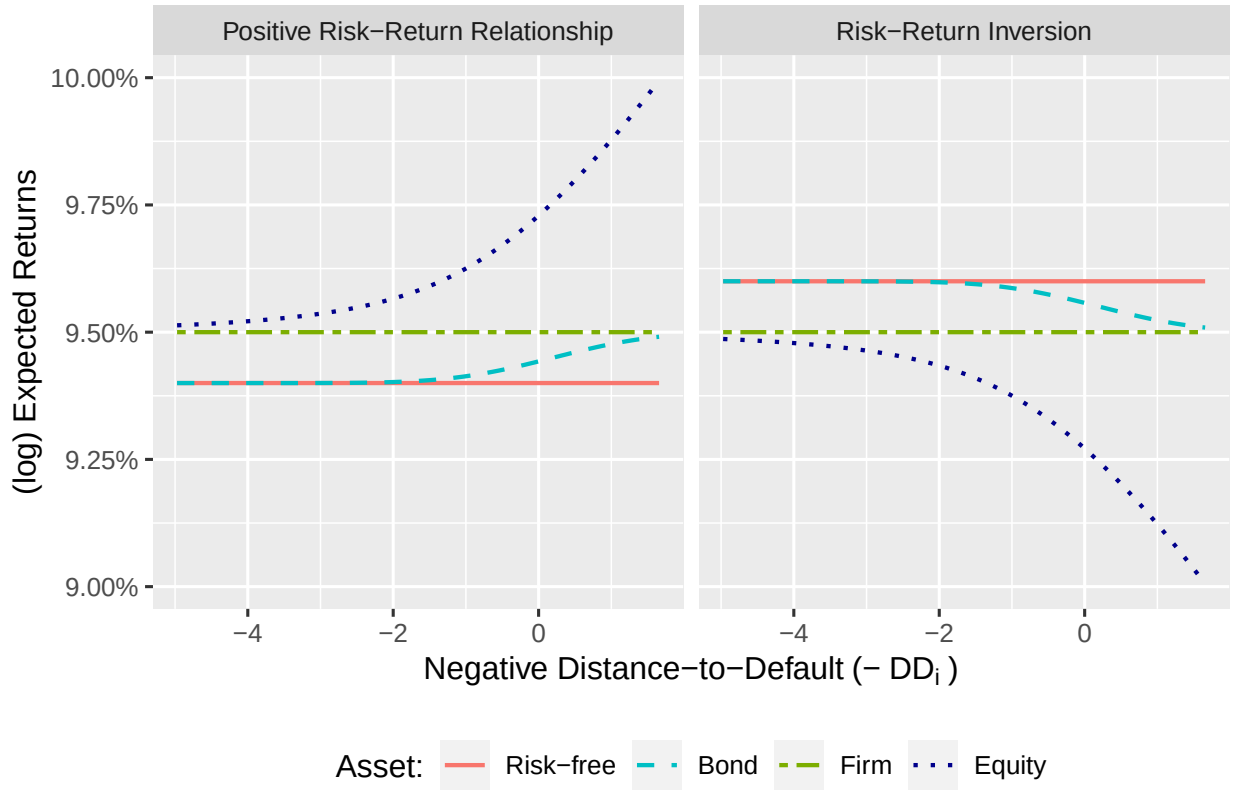


Figure 5. Expected Returns, Credit Spreads, and Capital Structure.

Panel A illustrates the theoretical relationship between a firm's risk, measured as the negative of the firm's distance-to-default, and the expected returns on a firm's total assets ($\log E[R_{iT}]$), bonds ($\log E[R^D_{iT}]$), equity ($\log E[R^E_{iT}]$), and the risk-free bond yield (y^f). The left-hand figure of Panel A presents an economy with a positive risk-return relationship ($\gamma\sigma_C^2 - \delta\theta > 0$), and the right-hand figure presents an economy with a negative risk-return relationship ($\gamma\sigma_C^2 - \delta\theta < 0$). The parameters are: $\delta = 0.01$, $\gamma = 1$, $\sigma_I = 0.4$, $\sigma_C = 0.1$. Panel B illustrates the theoretical relationship between a firm's risk, measure as the negative of the firm's distance-to-default, and the credit spread on the firm's bonds in three scenarios: a positive risk premium, a risk premium of zero (meaning the credit spread equals the expected loss on the bond), and a negative risk premium.

Panel A: Expected Returns and Capital Structure



Panel B: Credit Spreads and Capital Structure

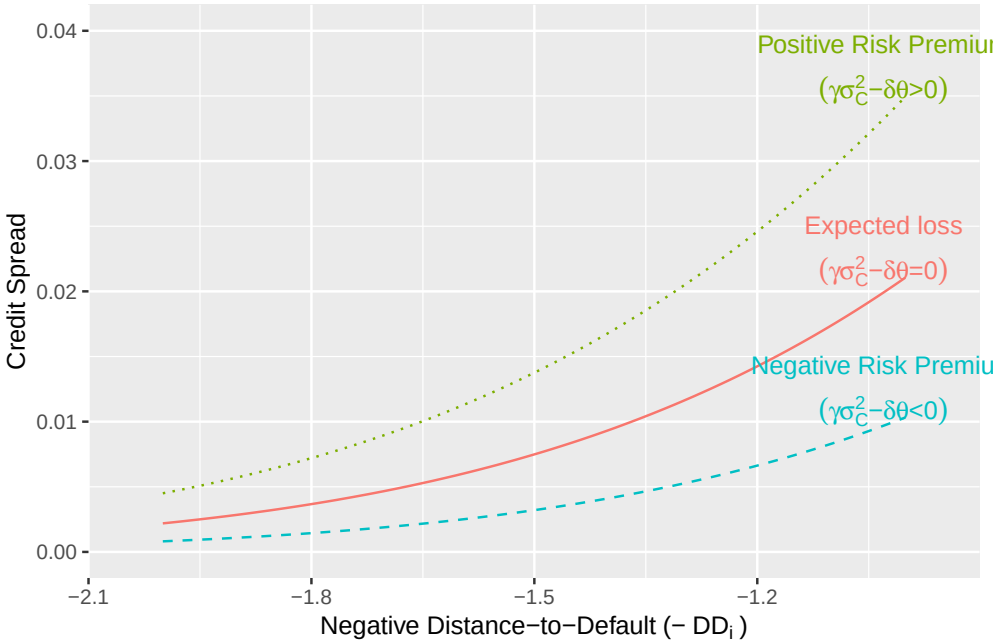


Table 1. Summary Statistics.

This table presents summary statistics for my sample of monthly returns, yields and characteristics of senior unsecured bonds issued by non-financial firms from January 1976 to July 2024. The sample includes information of 954 individual firms and 11,967 individual bonds. The panel is constructed using information from the Lehman/Warga database (January 1976-December 1996), the ICE Bank of America Fixed Income Indices (January 1997-June 2002) and WRDS Corporate Bond Panel (TRACE) (July 2002-July 2024).

				Percentile				
	N	Mean	SD	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
Bond Level Variables								
Yield: y_{ijt} (%)	719,746	4.8	2.3	0.8	3.2	4.6	6.1	11.8
Credit Spread: (%)	719,746	1.5	1.0	0.2	0.8	1.3	1.9	5.1
Duration (years)	719,746	7.5	4.1	1.9	4.1	6.4	10.7	17.4
Time to Maturity (years)	719,746	11.6	8.6	2.1	4.6	8.1	18.7	29.6
Monthly Bond Return (%)	719,746	0.4	2.6	−6.9	−0.5	0.4	1.5	8.1
Rating Number	719,746	7.3	2.0	1.0	6.0	8.0	9.0	10.0
Firm Level Variables								
Distance to default: $\widetilde{DD}_{it}$	182,159	9.0	5.5	0.4	5.2	8.0	11.6	26.9
Number of Bonds per Firm	182,159	10.6	14.1	1.0	2	5	13	65.0
Monthly Equity Return (%)	182,159	1.0	8.1	−20.8	−3.4	1.1	5.4	22.6
Macro Variables								
Yield for Risk: YFR_t (bp)	579	6.7	4.4	0.4	3.8	6.0	8.5	23.1
Excess Bond Market Return (%)	579	0.3	1.7	−4.3	−0.5	0.4	1.2	5.0
Excess Equity Market Return (%)	579	0.7	4.5	−11.0	−1.9	1.1	3.5	10.9

Table 2. Yield-for-Risk and the State of the Market

This table presents the results of the regression:

$$YFR_t = \alpha + \beta \times X_t + \epsilon_t$$

where YFR_t is yield-for-risk (measured in basis points), and X_t represents a range of explanatory variables capturing the state of the economy. The explanatory variables are: (1) "Past defaults" which measures the issuer-weighted default rate for all corporates over the past year (available annually, source: Moody's Investors Service), (2) "Tightening lending standards" which is the net fraction of banks that have reported tightened lending standards minus the fraction banks that have reported loosening lending standards over the past quarter (available quarterly, source: The Federal Reserve's Senior Loan Officer Opinion Survey), (3) "Bond market return" which is the excess return of the bond market over the previous three years (available monthly, source: Own bond panel), and (4) "The equity market returns" which is the excess return on the equity market over the previous three years (available monthly, source: Ken R. French's data library). t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with 5 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that low levels of YFR_t are associated with low past defaults, loose lending standards, and high bond and equity market returns.

	YFR_t			
	(1)	(2)	(3)	(4)
Past defaults	2.09^{***}			
	[2.67]			
Tightening lending standards		0.12^{***}		
		[5.94]		
Bond market return			-0.15^{**}	
			[−2.49]	
Equity market return				-0.36^{***}
				[−5.03]
Observations	44	136	543	543
R^2	0.23	0.45	0.03	0.28

Table 3. Predicting Returns to Credit Risk in the Cross-Section

This table presents the results of the return forecasting regression:

$$r_{t+h}^{20\%\ riskiest} - r_{t+h}^{20\%\ safest} = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \epsilon_{t+h}$$

where $r_{t+h}^{20\%\ riskiest}$ is the average h-month return of assets issued by 20% riskiest firms at time t as measured by distance-to-default, while $r_{t+h}^{20\%\ safest}$ is the average h-month return of the assets issued by the 20% safest firms at time t. Panel A presents the results when measuring the corporate bond returns of the riskiest over the safest firms. Panel B repeats the analysis using the equity returns of the riskiest over the safest firms. The regressors are yield-for-risk, YFR_t, as estimated from equation (1) and normalized by its standard deviation, the change in the 10-year Treasury yield, $\Delta_h y_{t+h}^{10}$, from year t to $t+h$, and the change in the slope of the Treasury yield curve, $\Delta_h(y_{t+h}^{10} - y_{t+h}^{1})$, from year t to $t+h$. The slope of the Treasury yield curve is measured as the difference between the 10-year and 1-year Treasury yield. t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with lags of 0, 9, 18 months for prediction horizons 1, 6 and 12 months, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that yield-for-risk strongly predicts returns to credit risk in the cross-section of both corporate bonds and equities.

Panel A: *Predicting returns to credit risk in the cross-section: Corporate Bonds*

	Horizon (h)					
	1-month returns		6-month returns		12-month returns	
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	0.15**	0.14**	1.09***	1.01***	1.83***	1.72***
	[2.20]	[2.13]	[5.16]	[4.83]	[5.10]	[5.19]
$\Delta_h y_{t+h}^{10}$		0.27***		0.72***		1.04***
		[6.55]		[3.50]		[3.74]
$\Delta_h(y_{t+h}^{10} - y_{t+h}^{1})$		0.09**		0.11		0.03
		[2.02]		[0.83]		[0.16]
Observations	579	579	579	579	579	578
Adjusted R^2	0.03	0.12	0.18	0.27	0.27	0.38

Table 3: Predicting Returns to Credit Risk in the Cross-Section *(Continued)*

Panel B: *Predicting returns to credit risk in the cross-section: Equities*

	Horizon (h)					
	1-month returns		6-month returns		12-month returns	
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	0.74***	0.68***	4.45***	3.97***	7.91***	7.55***
	[2.90]	[2.78]	[4.62]	[4.33]	[5.77]	[5.70]
$\Delta_h y^{10}_{t+h}$		0.45**		2.16***		3.25**
		[2.49]		[2.60]		[2.48]
$\Delta_h(y^{10}_{t+h} - y^{1}_{t+h})$		0.60***		1.58*		0.18
		[2.85]		[1.89]		[0.16]
Observations	579	579	579	579	579	578
Adjusted R^2	0.03	0.06	0.16	0.22	0.24	0.29

Table 4. Yield-for-risk vs. Alternative Measures of Sentiment

This table presents the results of the return forecasting regression:

$$r_{t+12}^{20\%\ riskiest} - r_{t+12}^{20\%\ safest} = \alpha + \beta \times YFR_t + \delta^T Z_t + \epsilon_{t+h}$$

For columns (1)-(5), $r_{t+12}^{20\%\ riskiest} - r_{t+12}^{20\%\ safest}$ is the average 12-month return of the bonds issued by the 20% riskiest firms over the average 12-month return of the bonds issued by the 20% safest firms. For columns (6)-(10), $r_{t+12}^{20\%\ riskiest} - r_{t+12}^{20\%\ safest}$ is the 12-month returns of the 20% riskiest equities over the 20% safest equities. The yield-for-risk parameter YFR_t is estimated from equation (1). The vector Z_t contains the alternative return predictors: the excess bond premium (Gilchrist and Zakrajšek (2012)), the high yield share (Greenwood and Hanson (2013)), the VIX, and the average spread between BAA rated bonds and 10-year Treasury yield. All regressors are normalized by their standard deviation. t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with 18 months lags for prediction. Regressions with HYS as regressor are quarterly and include 6 quarterly lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that the predictive power of yield-for-risk on returns to credit risk is not subsumed by other known measures of credit market sentiment.

	12-month bond portfolio returns					12-month equity portfolio returns				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
YFR_t	1.89***	1.73***	1.89***	1.70***	1.81***	8.05***	8.23***	6.09***	7.34***	8.08***
	[5.55]	[4.76]	[4.43]	[4.60]	[3.52]	[4.91]	[8.57]	[4.46]	[5.36]	[6.73]
Excess Bond Premium	−0.11				0.03	−0.24				2.65*
	[−0.30]				[0.08]	[−0.15]				[1.84]
High Yield Share		0.46*			0.69**		−0.04			1.92
		[1.84]			[2.00]		[−0.04]			[1.48]
VIX			0.10		−0.63			3.66*		−1.02
			[0.20]		[−1.55]			[1.89]		[−0.81]
BAA spread				0.27	0.77				1.23	−1.30
				[0.78]	[1.31]				[0.83]	[−0.90]
Observations	579	131	413	579	105	579	131	413	579	105
Adjusted R^2	0.27	0.23	0.28	0.28	0.26	0.24	0.37	0.33	0.25	0.41

Table 5. Predicting Returns to the Aggregate Bond Market

This table presents the results of the forecasting regression:

$$r_{t+h}^{mkt} - y_t^{f,h} = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \delta^T Z_t + \epsilon_{t+h} \tag{24}$$

where r_{t+h}^{mkt} is the return on the aggregate bond market from time t to $t+h$, $y_t^{f,h}$ is the h-month Treasury yield at time t, YFR_t is yield-for-risk (normalized), X_{t+h} contains the change in the 10-year Treasury yield, and the change in the difference between the 10-year and the 1-year Treasury yield. Z_t contains the Excess Bond Premium (Gilchrist and Zakrajšek, 2012), the High Yield Share (Greenwood and Hanson, 2013), the CBOE VIX, and the BAA Spread. t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with lags of 0, 9, 18 months for prediction horizons 1, 6 and 12 months, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that yield-for-risk is a strong predictor of the aggregate bond market.

Panel A: *Predicting returns to the aggregate corporate bond market*

	Horizon					
	1-month returns		6-month returns		12-month returns	
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	0.23^{***}	0.25^{***}	1.29^{***}	1.57^{***}	2.07^{***}	2.64^{***}
	[4.04]	[4.92]	[3.62]	[5.18]	[3.02]	[4.92]
$\Delta_h y_{t+h}^{10}$		-1.25^{***}		-3.19^{***}		-4.98^{***}
		[−24.06]		[−14.70]		[−13.19]
$\Delta_h(y_{t+h}^{10} - y_{t+h}^{1})$		0.10^{*}		−0.09		−0.45
		[1.76]		[−0.51]		[−1.01]
Constant	−0.05	−0.10	−0.43	-0.99^{**}	−0.29	−1.44
	[−0.48]	[−1.36]	[−0.61]	[−2.01]	[−0.23]	[−1.54]
Observations	579	579	579	579	579	578
Adjusted R^2	0.02	0.63	0.08	0.66	0.09	0.69

Table 5: Predicting Returns to the Aggregate Bond Market (Continued)

Panel B: *Robustness of bond market return predictability*

	12 month bond market returns				
	(1)	(2)	(3)	(4)	(5)
YFR_t	1.79***	2.90***	2.88***	1.50***	2.48***
	[4.64]	[4.42]	[5.61]	[3.92]	[4.47]
Excess Bond Premium	1.61***				0.12
	[3.80]				[0.14]
High Yield Share		−0.24			−0.37
		[−0.88]			[−0.53]
VIX			0.40		−0.42
			[0.61]		[−0.70]
BAA spread				2.54***	1.37
				[6.46]	[1.19]
Constant	−0.30	−0.32	−2.59	−6.70***	−2.33
	[−0.38]	[−0.24]	[−1.48]	[−5.60]	[−0.69]
Treasury term structure controls	Y	Y	Y	Y	Y
Observations	578	131	412	578	105
Adjusted R^2	0.72	0.59	0.60	0.76	0.56

Table 6. Debt Issuance and Yield-for-Risk

This table presents the results of the regression model:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \delta^T Z_{it} + \epsilon_{it+3} \tag{25}$$

where $Issuance_{it+3}$ is the 3-month net debt issuance by company i from t to $t+3$, and YFR_t is yield-for-risk at time t normalized by its standard deviation. Z_{it} is a vector of control variables which include the firm's cash, net income and EBITDA, as well as 4 lags of the dependent variable or a company fixed effect. The right-hand panel runs an alternative OLS specification with average issuance as dependent variable. t-statistics are reported in the brackets based on Driscoll and Kraay (1998) standard errors for panel regressions and Newey and West (1987) standard errors for OLS with 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that yield-for-risk predicts net debt issuance.

	Panel				OLS	
	Net Issuance$_{t+3}$			ΔTotal Liab.	Net Issuance$_{t+3}$	ΔTotal Liab.
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	−0.31***	−0.29***	−0.26***	−0.47***	−0.19***	−0.24***
	[−5.56]	[−5.94]	[−5.22]	[−4.91]	[−4.95]	[−4.12]
Risk free rate		0.03	0.04	0.07*	−0.01	0.01
		[1.42]	[1.35]	[1.84]	[−0.49]	[1.20]
Cash and Short-term Investments		−0.01***	−0.01***	0.001		
		[−3.91]	[−3.26]	[0.31]		
Net Income		−0.004	0.02***	0.01		
		[−0.70]	[3.08]	[1.18]		
EBITDA		−0.03***	−0.02***	−0.04***		
		[−6.10]	[−3.73]	[−7.56]		
Lags of dependent var	0	4	0	4	4	4
Fixed Effects			Firm			
R2	0.00	0.01	0.00	0.02	0.42	0.50
Observations	116,025	116,025	116,025	135,047	158	192

Table 7. Issuance by Risky Firms

This table presents the results of the regression model:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \chi \times Risk_{it} + \xi \times YFR_t \times Risk_{it} + \delta^T Z_{it} + \epsilon_{it+3} \quad (26)$$

where $Issuance_{it+3}$ is the 3-month net debt issuance by company i from t to $t+3$, YFR_t is yield-for-risk at time t (normalized), and Z_{it} is the same vector of control variables as in Table 6. $Risk_{it}$ is measures the fraction of firm's safer than firm i at time t. t-statistics are reported in the brackets based on Driscoll and Kraay (1998) standard errors with 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that the net debt issuance of the riskiest firms is more sensitive yield-for-risk than the net debt issuance of the safest firms.

	Net Issuance$_{t+3}$			ΔTotal Liab.
	(1)	(2)	(3)	(4)
YFR_t	-0.20^{***}	-0.20^{***}	-0.20^{***}	-0.42^{***}
	[−5.33]	[−5.36]	[−5.27]	[−5.31]
$Risk_{it}$	-0.71^{***}	-0.74^{***}	-1.11^{***}	-2.21^{***}
	[−5.54]	[−6.65]	[−10.10]	[−12.71]
$YFR_t \times Risk_{it}$	-0.23^{**}	-0.23^{**}	-0.25^{**}	-0.21^{**}
	[−2.19]	[−2.29]	[−2.37]	[−2.02]
Cash and Short-term Investments			-0.01^{***}	-0.01^{***}
			[−6.85]	[−3.57]
Net Income			-0.02^{***}	−0.02
			[−3.76]	[−1.60]
EBITDA			-0.03^{***}	-0.05^{***}
			[−6.68]	[−8.55]
Lags of dependent var	0	4	4	4
R2	0.00	0.01	0.01	0.02
Observations	116,025	116,025	116,025	135,047

Appendix A: Additional Empirical Results

Table A1. Robustness of Return Predictability to Specification

This table presents the results of different specifications of the regression model:

$$r_{t+12}^{n\%\ riskiest} - r_{t+12}^{n\%\ safest} = \alpha + \beta \times YFR_t + \epsilon_{t+h}$$

where $r_{t+12}^{n\%\ riskiest}$ is the average 12-month return of all firms with distance-to-default below the n'th percentile, and $r_{t+12}^{n\%\ safest}$ is the average 12-month return of all firms with distance-to-default above the $(100-n)$'th percentile. The table presents results for three alternative portfolio methodologies: (1) Equal-weighted returns, (2) Value-weighted returns, and (3) Equal-weighted returns hedged against changes in the Treasury yield. Panel A presents results for bond portfolios. Panel B presents results for equity portfolios. t-statistics are based on Newey and West (1987) standard errors with 0, 9 and 18 lags for forecasting horizons of 1 month, 6 months and 12 months, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that the predictive power of YFR_t on credit risk in the cross-section of bonds and stocks is robust to alternative specifications of the forecasting regression model.

Panel A: *Predicting returns to credit risk: Corporate Bonds*

	Equal-weighted returns					
	1-month		6-month		12-month	
Portfolio threshold (n)	δ	t-statistic	δ	t-statistic	δ	t-statistic
0.15	0.15	1.9*	1.20	5.2***	1.97	4.8***
0.20	**0.15**	**2.2****	**1.09**	**5.2*****	**1.83**	**5.1*****
0.25	0.13	2.1**	0.95	5.0***	1.60	5.0***
0.30	0.11	2.1**	0.86	4.9***	1.45	5.0***
0.35	0.10	2.0**	0.77	4.8***	1.30	4.9***

	Value-weighted returns					
	1-month		6-month		12-month	
Portfolio threshold (n)	δ	t-statistic	δ	t-statistic	δ	t-statistic
0.15	0.18	2.1**	1.26	5.3***	2.05	4.8***
0.20	0.21	2.5**	1.21	5.5***	1.98	5.2***
0.25	0.19	2.6**	1.09	5.2***	1.79	5.1***
0.30	0.16	2.4**	0.99	5.2***	1.62	5.2***
0.35	0.15	2.3**	0.90	5.2***	1.48	5.1***

	Returns hedged against changes in risk-free rate					
	1-month		6-month		12-month	
Portfolio threshold (n)	δ	t-statistic	δ	t-statistic	δ	t-statistic
0.15	0.14	1.8*	1.09	4.5***	1.86	4.3***
0.20	0.15	2.1**	0.98	4.4***	1.67	4.3***
0.25	0.12	2.0**	0.86	4.3***	1.49	4.3***
0.30	0.10	1.9*	0.79	4.3***	1.36	4.4***
0.35	0.09	1.9*	0.70	4.1***	1.21	4.2***

Table A1: Robustness of Return Predictability to Specification (Continued)

Panel B: *Predicting returns to credit risk: Equities*

Equal-weighted returns

	1-month		6-month		12-month	
Portfolio threshold (n)	δ	t-statistic	δ	t-statistic	δ	t-statistic
0.15	0.86	3.0***	4.93	4.6***	8.96	5.7***
0.20	**0.74**	**2.9*****	**4.45**	**4.6*****	**7.91**	**5.8*****
0.25	0.70	3.1***	4.06	4.6***	7.28	5.8***
0.30	0.65	3.2***	3.86	4.8***	6.97	6.2***
0.35	0.58	3.1***	3.50	5.0***	6.41	6.4***

Value-weighted returns

	1-month		6-month		12-month	
Portfolio threshold (n)	δ	t-statistic	δ	t-statistic	δ	t-statistic
0.15	0.78	2.7***	4.51	3.9***	7.85	4.2***
0.20	0.59	2.2**	3.89	3.6***	6.44	3.7***
0.25	0.56	2.3**	3.39	3.4***	5.74	3.6***
0.30	0.48	2.1**	3.16	3.5***	5.30	3.8***
0.35	0.44	2.1**	2.64	3.3***	4.43	3.6***

Returns hedged against changes in risk-free rate

	1-month		6-month		12-month	
Portfolio threshold (n)	δ	t-statistic	δ	t-statistic	δ	t-statistic
0.15	0.94	3.6***	5.75	7.1***	9.06	6.2***
0.20	0.81	3.4***	5.18	7.3***	8.00	6.4***
0.25	0.77	3.6***	4.70	7.0***	7.27	6.5***
0.30	0.72	3.7***	4.44	7.4***	6.87	6.8***
0.35	0.64	3.7***	3.97	7.3***	6.24	6.7***

Table A2. Robustness of Thresholds for Risk-Return Inversion

This table presents the results of different specifications of the regression model:

$$r_{t+12}^{n\%\ riskiest} - r_{t+12}^{n\%\ safest} = \lambda^{Low} \times 1_{\{YFR_t \leq m\text{'th percentile}\}} + \lambda^{Mid} \times 1_{\{m\text{'th percentile} < YFR_t \leq (100-m)\text{'th percentile}\}} + \lambda^{High} \times 1_{\{YFR_t > (100-m)\text{'th percentile}\}} + \epsilon_{t+12}$$

where $r_{t+12}^{n\%\ riskiest}$ is the average 12-month return of all firms with distance-to-default below the n'th percentile, and $r_{t+12}^{n\%\ safest}$ is the average 12-month return of all firms with distance-to-default above the $(100-n)$'th percentile. $1_{\{YFR_t \leq m\text{'th percentile}\}}$, $1_{\{YFR_t > m\text{'th percentile}\}}$ and $1_{\{m\text{'th percentile} < YFR_t \leq (100-m)\text{'th percentile}\}}$ are indicator variables that switch on if YFR_t is below its m'th, above its $(100-m)$'th or in between its m'th and $(100-m)$'th percentile, respectively. t-statistics are based on Newey and West (1987) standard errors with 18 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that risk-return inversion is robust for both asset classes across specifications.

Panel A: *Risk-Return Inversion: Corporate Bonds*

	YFR_t indicator threshold (m)							
	0.20	0.25	0.30	0.35	0.20	0.25	0.30	0.35
Portfolio threshold (n)	λ^{Low}				$t(\lambda^{Low})$			
0.15	-1.0	-0.9	-0.9	-0.9	-2.4**	-2.5**	-2.8***	-2.5**
0.20	-0.9	**-0.8**	-0.8	-0.8	-2.7***	**-2.8*****	-3.0***	-2.7***
0.25	-0.7	-0.7	-0.6	-0.6	-2.3**	-2.4**	-2.6**	-2.2**
0.30	-0.6	-0.6	-0.5	-0.5	-1.9*	-2.0**	-2.2**	-1.9*
0.35	-0.5	-0.5	-0.5	-0.4	-1.6	-1.8*	-2.0**	-1.8*
	λ^{Mid}				$t(\lambda^{Mid})$			
0.15	-0.1	-0.2	-0.4	-0.4	-0.1	-0.5	-0.7	-0.7
0.20	0.0	-0.1	-0.3	-0.3	0.1	-0.3	-0.6	-0.6
0.25	0.0	-0.1	-0.2	-0.3	0.1	-0.3	-0.5	-0.5
0.30	0.1	0.0	-0.1	-0.1	0.3	0.0	-0.3	-0.3
0.35	0.1	0.1	-0.1	-0.1	0.4	0.2	-0.2	-0.2
	λ^{High}				$t(\lambda^{High})$			
0.15	3.7	3.4	3.1	2.7	2.9***	3.2***	3.5***	3.5***
0.20	3.4	**3.2**	2.9	2.5	3.1***	**3.5*****	3.7***	3.7***
0.25	3.1	2.9	2.6	2.3	3.2***	3.5***	3.7***	3.7***
0.30	2.9	2.6	2.4	2.1	3.3***	3.6***	3.9***	3.9***
0.35	2.6	2.4	2.2	1.9	3.3***	3.6***	3.9***	3.9***

Table A2: Robustness of Thresholds for Risk-Return Inversion (Continued)

Panel B: *Risk-Return Inversion: Equities*

	YFR_t indicator threshold (m)							
	0.20	0.25	0.30	0.35	0.20	0.25	0.30	0.35
Portfolio threshold (n)	λ^{Low}				$t(\lambda^{Low})$			
0.15	-8.7	-7.9	-7.1	-5.5	-3.5***	-3.7***	-3.5***	-2.7***
0.20	-8.3	**-7.4**	-6.5	-5.1	-4.2***	**-4.3*****	-4.0***	-3.0***
0.25	-8.0	-7.2	-6.2	-4.8	-4.8***	-5.0***	-4.4***	-3.3***
0.30	-7.9	-7.1	-6.1	-4.9	-4.8***	-4.9***	-4.3***	-3.4***
0.35	-7.3	-6.7	-5.8	-4.7	-4.6***	-4.8***	-4.3***	-3.5***
	λ^{Mid}				$t(\lambda^{Mid})$			
0.15	1.2	1.3	1.0	0.0	0.7	0.6	0.4	0.0
0.20	1.0	1.0	0.7	-0.2	0.6	0.6	0.4	-0.1
0.25	1.3	1.3	0.9	0.0	0.9	0.8	0.5	0.0
0.30	1.1	1.0	0.6	0.0	0.8	0.7	0.4	0.0
0.35	0.9	0.9	0.5	-0.1	0.7	0.7	0.3	-0.1
	λ^{High}				$t(\lambda^{High})$			
0.15	16.9	14.9	13.7	12.3	3.5***	3.5***	3.7***	3.7***
0.20	14.9	**13.0**	12.0	10.7	3.6***	**3.5*****	3.7***	3.7***
0.25	13.6	12.3	11.3	10.2	3.7***	3.7***	4.0***	3.9***
0.30	12.5	11.4	10.5	9.3	3.7***	3.8***	4.1***	3.9***
0.35	11.2	10.2	9.5	8.6	3.8***	4.0***	4.2***	4.1***

Table A3. Bootstrapped p-values and Finite Sample Bias Adjustments

This table presents p-values and biases for the coefficient estimates from my main linear return prediction model:

$$r_{t+h}^{High\ Risk} - r_{t+h}^{Low\ Risk} = \alpha + \beta^{(h)} \times YFR_t + \zeta^T X_{t+h} + \epsilon_{t+h}$$

and the test for average 12-month returns by yield-for-risk quartile from Figure 1:

$$r_{t+12}^{High\ Risk} - r_{t+12}^{Low\ Risk} = \sum_{i=1}^{4} \lambda_i 1_{\{YFR_t \text{ in } i\text{'th quartile}\}} + \epsilon_{t+h}$$

The table presents the p-values calculated using standard asymptotics, "fixed-b" asymptotics as in Kiefer and Vogelsang (2005), and p-values calculated using the block bootstrap method described in the main text with 100,000 samples, and block sizes being drawn from a geometric distribution with success probability 1/12. t-statistics are calculated using Newey and West (1987) standard errors with 0, 9 and 18 lags for 1-, 6-, and 12-month forecasting horizon. The table also presents the bootstrap bias estimates for all regression coefficients, and the Boudoukh, Israel, and Richardson (2020) (BIR2020) estimate of the Stambaugh (1999) bias for the univariate linear regressions. Panel A and B present the results for bond returns and equity returns, respectively. The table shows that finite sample biases such as Stambaugh (1999) are not driving the predictive power of yield-for-risk or the risk-return inversion.

Panel A: *Return of riskiest bonds over safest bonds*

	Linear Regression			Regression on YFR_t quartile			
	1-month	6-month	12-month	12-month			
	$\delta^{(1)}$	$\delta^{(6)}$	$\delta^{(12)}$	β_1	β_2	β_3	β_4
Coefficient estimate	0.15	1.09	1.83	-0.82	-0.41	0.15	3.18
t-statistic	[2.2]	[5.2]	[5.1]	[-2.8]	[-0.8]	[0.4]	[3.5]
$P(>\|t\|)$ asymptotic	(0.028)	(0.000)	(0.000)	(0.005)	(0.445)	(0.726)	(0.001)
$P(>\|t\|)$ fixed-b	(0.013)	(0.000)	(0.000)	(0.006)	(0.623)	(0.432)	(0.007)
$P(>\|t\|)$ bootstrap	(0.022)	(0.000)	(0.000)	(0.015)	(0.555)	(0.923)	(0.007)
Bias (bootstrap)	0.00	0.01	0.01	-0.01	0.05	-0.07	0.04
Bias (BIR2020)	0.01	0.05	0.08				

Panel B: *Return of riskiest equities over safest equities*

	Linear Regression			Regression on YFR_t quartile			
	1-month	6-month	12-month	12-month			
	$\delta^{(1)}$	$\delta^{(6)}$	$\delta^{(12)}$	β_1	β_2	β_3	β_4
Coefficient estimate	0.74	4.45	7.91	-7.44	0.94	1.14	13.04
t-statistic	[2.9]	[4.6]	[5.8]	[-4.3]	[0.5]	[0.5]	[3.5]
$P(>\|t\|)$ asymptotic	(0.004)	(0.000)	(0.000)	(0.000)	(0.607)	(0.650)	(0.001)
$P(>\|t\|)$ fixed-b	(0.008)	(0.000)	(0.000)	(0.000)	(0.842)	(0.106)	(0.002)
$P(>\|t\|)$ bootstrap	(0.000)	(0.000)	(0.000)	(0.001)	(0.530)	(0.761)	(0.003)
Bias (bootstrap)	0.01	0.03	0.04	-0.32	0.41	-0.07	0.03
Bias (BIR2020)	0.01	0.04	0.08				

Table A4. Excess Debt Issuance.

This table presents alternative specifications of the regression model used to generate Figure 4:

$$Issuance_{it+3} = \sum_{k=1}^{5} (\chi_k + \xi_k \times 1_{\{\text{Low } YFR_t\}}) \times 1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}} + \delta^T Z_{it} + \epsilon_{it+3}$$

where Z_{it} contains control variables, consisting of the 10-year Treasury yield, four lags of the dependent variable, and controls for the strength of the firms balance sheet (cash, net income and EBITDA). $1_{\{\text{Low } YFR_t\}}$ is an indicator variable, which takes the value of one if YFR_t is in its lowest quartile. $1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}}$ is an indicator variable that switches on if $\widetilde{DD}_{it}$ is in the k'th quintile at time t. t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) standard errors using 4 lags and Kiefer and Vogelsang (2005) "fixed-b" asymptotics.

	Net Debt Issuance$_{t+3}$				
	(1)	(2)	(3)	(4)	(5)
Risk Quintile 1	−0.02	−0.12	−0.14	0.04	0.02
	[−0.19]	[−1.02]	[−1.20]	[0.34]	[0.17]
Risk Quintile 2	0.30***	0.20	0.19	0.43***	0.42***
	[2.69]	[1.55]	[1.51]	[3.14]	[3.14]
Risk Quintile 3	0.49***	0.39***	0.38***	0.68***	0.67***
	[4.68]	[3.28]	[3.23]	[5.06]	[5.05]
Risk Quintile 4	0.63***	0.53***	0.53***	0.87***	0.87***
	[7.34]	[4.86]	[4.83]	[7.17]	[7.12]
Risk Quintile 5	0.72***	0.62***	0.63***	1.08***	1.08***
	[10.09]	[5.46]	[5.53]	[8.81]	[8.77]
Risk Quintile 1×low_YFR_t	0.78**	0.65**	0.65**	0.66**	0.66***
	[2.55]	[2.49]	[2.57]	[2.56]	[2.65]
Risk Quintile 2×low_YFR_t	0.90***	0.77***	0.78***	0.78***	0.79***
	[4.97]	[4.68]	[4.89]	[4.97]	[5.19]
Risk Quintile 3×low_YFR_t	0.70***	0.56***	0.58***	0.58***	0.59***
	[3.19]	[2.99]	[3.11]	[3.09]	[3.21]
Risk Quintile 4×low_YFR_t	0.39*	0.25	0.27	0.27	0.28
	[1.84]	[1.23]	[1.28]	[1.34]	[1.39]
Risk Quintile 5×low_YFR_t	0.28**	0.14	0.15	0.13	0.14
	[2.43]	[0.99]	[1.06]	[0.93]	[0.98]
Balance Sheet Controls	F	F	F	T	T
Risk-free rate control	F	T	T	T	T
Lags of dependent variable	0	0	4	0	4
Observations	116,025	116,025	116,025	116,025	116,025
R^2	0.01	0.01	0.02	0.02	0.02

Table A5. Stock Repurchases, Investments, Cash holdings and Yield-for-Risk

This table presents the results of the regression model:

$$y_{it+3} = \beta \times YFR_t + \gamma' Z_{it} + \epsilon_{it+3}$$

where $y_{it+3} \in \{\text{Net Equity Purchase}_{it+3}, \text{CAPX}_{it+3}, \text{Cash}_{it+3}\}$. Here, $\text{Net Equity Purchase}_{it+3}$ is the 3-month net equity purchase by company i from t to $t+3$, CAPX_{it+3} is the 3-month increase in capital expenditures by company i from t to $t+3$, and Cash_{it+3} is the increase in cash and short-term investments from t to $t+3$. The regressor YFR_t is yield-for-risk at time t, and Z_{it} is a vector of control variables which include the firm's net income and EBITDA, as well as 4 lags of the dependent variable. t-statistics are reported in the brackets based on Driscoll and Kraay (1998) standard errors for panel regressions and Newey and West (1987) standard errors for OLS with 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values.

	Large firms (Total Assets > 1bn. USD)						Small firms (Total Assets ≤ 1bn. USD)					
	Net Eq. Purch.$_{t+3}$		CAPX$_{t+3}$		Cash$_{t+3}$		Net Eq. Purch.$_{t+3}$		CAPX$_{t+3}$		Cash$_{t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
YFR_t	−0.15***	−0.14***	−0.13***	−0.09***	0.18***	0.23***	−0.01	−0.02	−0.20***	−0.06**	0.14	0.16
	[−5.29]	[−5.08]	[−3.38]	[−4.49]	[3.68]	[4.13]	[−0.20]	[−0.31]	[−3.91]	[−2.15]	[1.53]	[1.52]
Risk free rate		−0.04***		0.002		0.01		−0.05		0.01		0.01
		[−2.79]		[0.22]		[0.62]		[−0.90]		[0.87]		[0.17]
Net Income		0.09***		0.04***		0.03**		0.20***		0.03***		0.004
		[5.41]		[6.77]		[2.12]		[6.61]		[8.43]		[0.19]
EBITDA		−0.02***		−0.03***		0.03***		0.05***		−0.03***		0.04**
		[−2.70]		[−7.52]		[4.29]		[3.36]		[−7.71]		[2.46]
Lags of dependent variable	0	4	0	4	0	4	0	4	0	4	0	4
R2	0.00	0.08	0.00	0.65	0.00	0.04	0.00	0.07	0.01	0.41	0.00	0.01
Observations	43,490	43,490	49,375	49,375	49,662	49,662	54,724	54,724	65,606	65,606	66,337	66,337

Table A6. Comparing YFR_t to the EBP of Gilchrist and Zakrajšek (2012).

This table presents the results of the regression:

$$EBP_t = a + b \times \alpha_t + c \times YFR_t + \epsilon_t$$

where EBP_t is the excess bond premium of Gilchrist and Zakrajšek (2012), α_t and YFR_t are the results of the regression model (1) used to estimate yield-for-risk:

$$y_{ijt} - y^f_{jt} = \alpha_t + YFR_t \times (-\widetilde{DD}_{it}) + \gamma'_t Z_{ijt} + \epsilon_{ijt}. \quad \text{(A1)}$$

All variables have been normalized for ease of comparison. t-statistics are reported in the brackets and based on Newey and West (1987) standard errors using 12 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variable:	EBP		
Model:	(1)	(2)	(3)
Variables			
α_t	0.76***		0.69***
	(6.3)		(4.8)
YFR_t		0.57***	0.10
		(4.4)	(1.2)
Fit statistics			
Observations	576	576	576
R^2	0.574	0.328	0.580
Adjusted R^2	0.573	0.327	0.579

Appendix B: Proofs and additional theoretical results

The theoretical results of section 5 are derived by first proving the existence of a stochastic discount factor, m, which prices all assets in the economy. The stochastic discount factor is the result of the economy's equilibrium condition and the investor's first-order conditions.

Proposition 5 (**Stochastic Discount Factor**). *A unique equilibrium exists where the price of any time-T payoff X can be written as $P = E^{\theta}[mX]$, where the stochastic discount factor, m, is given by:*

$$m = \exp\{-\gamma[\delta + \frac{1}{2}\sigma_I^2 + \epsilon_C]\}$$

and E^{θ} denotes the expectation formed under the diagnostic measure given in equation (20).

Having defined the stochastic discount factor m, the equilibrium risk-free rate is given from the representative investor's expectation of m.

Corollary 1. *The equilibrium risk-free (log) rate is:*

$$y^f = \gamma[\delta(1+\theta) + \frac{1}{2}\sigma_I^2] - \frac{1}{2}\gamma^2\sigma_C^2 \tag{B1}$$

The risk-free rate increases with the expected growth rate of the market ($\delta(1+\theta)+\frac{1}{2}\sigma_I^2$) as the investor becomes wealthier and requires a higher risk-free rate to postpone consumption. Diagnostic expectations affects the risk-free rate by amplifying the effect of the news, δ, about the market's future payoff. For example, if the investor receives good news, $\delta > 0$, diagnostic expectations causes the investor to overestimate the future payoff of the market and thus his future consumption. This, in turn, lead him to require a risk-free rate that is too high relative to what he would have required under rational expectations. Conversely, if the investor receives bad news he becomes too pessimistic about the future economy and the risk-free rate drops. Market volatility, σ_C, lowers the risk-free rate as the investor seeks to hedge against uncertainty by saving in the risk-free asset.

As I final theoretical result, we see that the expected return on a firm's equities are more sensitive to the change in a firm's leverage and than the expected return of firm's bonds.

Proposition 6 (**Risk Sensitivity**). *For low enough K_i, the expected return on equities is more sensitive to changes in risk than the expected returns on bonds:*

$$\left|\frac{\partial}{\partial K_i}E[R_i^E]\right| \geq \left|\frac{\partial}{\partial K_i}E[R_i^D]\right| \geq 0$$

Note that it is only in the special case, where the investor is effectively risk-neutral, $\theta = \frac{\gamma\sigma_C^2}{\delta}$, that the inequalities of Proposition 6 are not strict. The result implies that the predictive power of yield-for-risk, should be stronger in the equity markets relative debt markets, as the former is more sensitive to changes in the firm's capital structure.

Proof of Corollary 1 and Proposition 1

From expressions (14) and (B1, we get the distributions of the stochastic discount factor, m, the firm's underlying assets, as well as the sum of the two[29]:

$$\log m \sim N(-\gamma[\delta + \frac{1}{2}\sigma_I^2], \gamma^2\sigma_C^2), \tag{B2}$$

$$\log V_i \sim N(\delta, \sigma_I^2 + \sigma_C^2), \tag{B3}$$

$$\log m + \log V_i \sim N(\delta(1-\gamma) - \gamma\frac{1}{2}\sigma_I^2, \sigma_I^2 + (1-\gamma)^2\sigma_C^2). \tag{B4}$$

Corollary 1 and Proposition 1 the follow as a direct application of Lemma 1:

$$y^f = -\log\left(E^\theta[m]\right) \tag{B5}$$

$$= \gamma[\delta(1+\theta) + \frac{1}{2}\sigma_I^2] - \gamma^2\frac{1}{2}\sigma_C^2 \tag{B6}$$

$$\log E[V_i]/P_i^V - y^f = \gamma\sigma_C^2 - \delta\theta \tag{B7}$$

where the price, P_i^V, and the (rational) expected payoff, $E[V_i]$, of the firm's assets are:

$$P_i^V = E^\theta[mV_i] \tag{B8}$$

$$= \exp\left\{\delta(1-\gamma)(1+\theta) + \frac{1}{2}\sigma_I^2(1-\gamma) + \frac{1}{2}(1-\gamma)^2\sigma_C^2\right\} \tag{B9}$$

$$= \exp\left\{-y^f + \delta\theta - \gamma\sigma_C^2\right\} E[V_i] \tag{B10}$$

$$E[V_i] = \exp\left\{\delta + \frac{1}{2}\sigma_I^2 + \frac{1}{2}\sigma_C^2\right\} \tag{B11}$$

□

2.1 Proof of Proposition 2 and 3

To prove proposition 2 and 3, it is easiest to first derive the expression for the price of firm i's equity, P_i^E. We'll make use of the fact that the conditional distribution of the stochastic discount factor, m, is:

$$m|V_i \sim \log N\left(-\gamma[\delta + \frac{1}{2}\sigma_I^2] - \frac{\gamma\sigma_C^2}{\sigma_V^2}u_i, \gamma^2\frac{\sigma_C^2\sigma_I^2}{\sigma_V^2}\right). \tag{B12}$$

[29]We note that the $Cov(\log m, \log V_i) = -\gamma\sigma_C^2$.

Further, we'll use the following simplifying notation for the total payoff of firm i's assets:

$$\log V_i = \delta + u_i, \tag{B13}$$

where $u_i = \epsilon_C + \epsilon_i \sim N(0, \sigma_V^2)$ and $\sigma_V^2 = \sigma_C^2 + \sigma_I^2$. Further,

$$V_i^\theta = \exp\{\delta(1+\theta) + u_i\} \tag{B14}$$

be the payoff the investor believes the firm's total assets will generate.

2.1.1 The price of firm i's equity

We can find the price of firm i's equity using the stochastic discount factor from proposition 5:

$$\begin{aligned}
P_i^E &= E^\theta[m(V_i - K_i)^+] && \text{(B15)}\\
&= E^\theta[mV_i 1_{\{V_i > K_i\}}] - K_i E[m 1_{\{V_i > K_i\}}] && \text{(B16)}\\
&= P_i^V \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V} + \sigma_V\right) - \exp\{-r^f\} K_i \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}\right) && \text{(B17)}
\end{aligned}$$

The detailed steps of getting to (B17) are shown below. The first term of (B17) is found using the law of total expectation:

$$E^{\theta}[mV_i 1_{\{V_i>K_i\}}] \tag{B18}$$

$$= E^{\theta}[E^{\theta}[m|V_i]V_i 1_{\{V_i>K_i\}}] \tag{B19}$$

$$= E^{\theta}[\exp\left\{-\gamma[\delta+\frac{1}{2}\sigma_I^2]-\frac{\gamma\sigma_C^2}{\sigma_V^2}u_i+\frac{1}{2}\gamma^2\frac{\sigma_C^2\sigma_I^2}{\sigma_V^2}+\delta+u_i\right\}1_{\{V_i>K_i\}}] \tag{B20}$$

$$= e^{-\gamma[\delta(1+\theta)+\frac{1}{2}\sigma_I^2]+\frac{1}{2}\gamma^2\frac{\sigma_C^2\sigma_I^2}{\sigma_V^2}+\delta(1+\theta)}E^{\theta}[\exp\left\{\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V}\right\}1_{\{V_i>K_i\}}] \tag{B21}$$

$$= P_i^V e^{-\frac{1}{2}\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)^2}E^{\theta}[\exp\left\{\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V}\right\}1_{\{V_i>K_i\}}] \tag{B22}$$

$$= P_i^V e^{-\frac{1}{2}\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)^2}\int_{V_i^{\theta}=K_i}^{\infty}\exp\left\{\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V}\right\}df\left(\frac{u_i}{\sigma_V}\right) \tag{B23}$$

$$= P_i^V e^{-\frac{1}{2}\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)^2}\frac{1}{\sqrt{2\pi}}\int_{V_i^{\theta}=K_i}^{\infty}\exp\left\{\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V}-\frac{1}{2}\left(\frac{u_i}{\sigma_V}\right)^2\right\}d\left(\frac{u_i}{\sigma_V}\right) \tag{B24}$$

$$= P_i^V e^{-\frac{1}{2}\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)^2}\Phi\left(\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)-\frac{\log K_i-\delta(1+\theta)}{\sigma_V}\right)e^{\frac{1}{2}\left(\sigma_V-\frac{\gamma\sigma_C^2}{\sigma_V}\right)^2} \tag{B25}$$

$$= P_i^V\Phi\left(DD_i+\frac{\theta\delta}{\sigma_V}-\frac{\gamma\sigma_C^2}{\sigma_V}+\sigma_V\right) \tag{B26}$$

The second term in (B17) is derived in much the same way as the first term and only the main steps are presented here:

$$K_i E^{\theta}[m1_{\{V_i>K_i\}}] \tag{B27}$$

$$= K_i E^{\theta}[E^{\theta}[m|V_i]1_{\{V_i>K_i\}}] \tag{B28}$$

$$= e^{-y^f}K_i\exp\left\{-\frac{1}{2}\left(\frac{\gamma\sigma_C^2}{\sigma_V}\right)^2\right\}E^{\theta}[\exp\left\{\frac{\gamma\sigma_C^2}{\sigma_V}\frac{u_i}{\sigma_V}\right\}1_{\{V_i>K_i\}}] \tag{B29}$$

$$= e^{-y^f}K_i\Phi\left(DD_i+\frac{\theta\delta}{\sigma_V}-\frac{\gamma\sigma_C^2}{\sigma_V}\right) \tag{B30}$$

2.1.2 The price of firm i's bond

With the price of firm i's equity at hand, the price of firm i's bond is found as the difference between the value of the entire firm and the firm's equity:

$$P_i^D = P_i^V - P_i^E \tag{B31}$$

$$= P_i^V \left(1 - \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V} + \sigma_V\right)\right) + e^{-y^f} K_i \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}\right) \tag{B32}$$

$$= P_i^V \left(\Phi\left(-DD_i - \sigma_V + \frac{\gamma\sigma_C^2}{\sigma_V} - \frac{\theta\delta}{\sigma_V}\right)\right) + e^{-y^f} K_i \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}\right) \tag{B33}$$

Note that the Modigliani and Miller (1958) propositions hold in my model as the value of the firm is independent of the firm's capital structure.

2.1.3 Credit spreads expected returns on bonds and stocks

With prices of debt and equity given above, Proposition 2 and 3 follows from the definitions of yields and expected returns:

$$cs_i = \log\left(\frac{K_i}{P_i^D}\right) - y^f \tag{B34}$$

$$= -\log\left(\frac{P_i^D}{K_i}\right) - y^f \tag{B35}$$

$$= -\log\left(\frac{P_i^V}{\exp\{-y^f\}K_i}\Phi\left(-DD_i - \sigma_V + \frac{\gamma\sigma_C^2 - \theta\delta}{\sigma_V}\right) + \Phi\left(DD_i - \frac{\gamma\sigma_C^2 - \theta\delta}{\sigma_V}\right)\right) \tag{B36}$$

$$\tag{B37}$$

The expected excess return on firm i's bond is simply the difference between the bond's credit spread, and the (log) expected loss on the bond:

$$\begin{aligned}
\log E[R_i^D] - y^f &= \log E[\frac{\min\{V_i, K_i\}}{P_i^D}] - y^f \\
&= \log E[\frac{\min\{V_i, K_i\}}{K_i}\frac{K_i}{P_i^D}] - y^f \\
&= cs_i + \log E[\frac{\min\{V_i, K_i\}}{K_i}] \\
&= cs_i + \log E[1_{\{V_i > K_i\}} + 1_{\{V_i < K_i\}}\frac{V_i}{K_i}] \\
&= cs_i - el_i
\end{aligned}$$

where $el_i = -\log(E[1_{\{V_i>K_i\}} + 1_{\{V_i<K_i\}}\frac{V_i}{K_i}])$ is the (log) expected loss on the bonds.

The expected return on the firm i's stock is found using Modigliani and Miller (1958) Proposition 2.

□

Proof of Proposition 4

To prove Proposition 4 note that the expected return on debt, $E[R_i^D] = \frac{E[\min\{K_i, V_i\}]}{P_i^D}$, has the following limits:

$$\lim_{K_i \to 0} E[R_i^D] \to e^{y^f} \tag{B38}$$

$$\lim_{K_i \to \infty} E[R_i^D] \to E[R_i^V] \tag{B39}$$

where $E[R_i^V] = \frac{E[V_i]}{P_i^V}$ is the expected return on the firms total assets and e^{y^f} is the (gross) risk-free rate.[30]

Given that expected return on debt is monotonic in K_i, we see that if the investors expectations are sufficiently biased, $\theta\delta > \gamma\sigma_C^2$, the expected excess return on the firm's total assets is negative, $e^{y^f} > E[R_i^V]$, and thus, the expected return on a firm's debt is decreasing with the amount of leverage, K_i, that the firm has in its capital structure:

$$\theta\delta > \gamma\sigma_C^2 \Rightarrow e^{y^f} > E[R_i^V] \Rightarrow \frac{\partial}{\partial K_i} E[R_i^D] < 0$$

To prove that the expected return on equity is decreasing with leverage, $\frac{\partial}{\partial K_i} E[R_i^E] < 0$ when expectations are sufficiently biased, $\theta\delta > \gamma\sigma_C^2$, we simply note that equity is a levered bet on the firm's underlying assets:

$$E[R^E] = E[R_i^V] + L_i \left(E[R_i^V] - E[R_i^D] \right)$$

where $L_i = \frac{P_i^D}{P_i^E}$ is the leverage of the firm. Given the limits for the expected return on debt (B38) and (B39), we have that the expected return on the expected return on the firm's

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Proof. We can see this by using L'Hôpital's Rule:

$$\begin{aligned}
\lim_{K_i \to 0} R_i^D &= \lim_{K_i \to 0} \frac{E[D_i]}{P_i^D} \\
&= \lim_{K_i \to 0} \frac{\frac{\partial}{\partial K_i} E[D_i]}{\frac{\partial}{\partial K_i} P_i^D} \\
&= \lim_{K_i \to 0} \frac{\Phi(DD_i)}{\Phi(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}) e^{-y^f}} \\
&= e^{y^f}
\end{aligned}$$

Oppositely for $K_i \to \infty \Rightarrow \min\{K_i, V_i\} \to V_i \Rightarrow R_i^D \to R_i^V$. □

total assets is lower than the expected return on the firm's debt if $\theta\delta > \gamma\sigma_C^2$:

$$\theta\delta > \gamma\sigma_C^2 \Rightarrow E[R_i^V] - E[R_i^D] < 0$$

Therefore, as the firm increases it's leverage, the expected return on firm's equity falls.

□

Proof of Proposition 5

The first order condition to the investor's maximization problem (19) wrt. π_i^E is:

$$\frac{\partial}{\partial \pi_i^E}\{u(W_0 - \int_{\mathcal{A}}(\pi_i^E - 1)P_i^E d\mu_i - \int_{\mathcal{A}}(\pi_i^D - 1)P_i^D d\mu_i) \tag{B40}$$

$$+ E^\theta[u(\int_{\mathcal{A}} \pi_i^E (V_i - K_i)^+ d\mu_i + \int_{\mathcal{A}} \pi_i^D \min\{V_i, K_i\} d\mu_i)]\} = 0 \tag{B41}$$

Therefore,

$$P_i^E = E^\theta[\frac{u'(\int_{\mathcal{A}} \pi_i^E (V_i - K_i)^+ d\mu_i + \int_{\mathcal{A}} \pi_i^D \min\{V_i, K_i\} d\mu_i)}{u'(W_0 - \int_{\mathcal{A}}(\pi_i^E - 1)P_i^E d\mu_i - \int_{\mathcal{A}}(\pi_i^D - 1)P_i^D d\mu_i)}(V_i - K_i)^+] \tag{B42}$$

$$= E^\theta[\left(\int_{\mathcal{A}} V_i d\mu_i\right)^{-\gamma}(V_i - K_i)^+] \tag{B43}$$

$$= E^\theta[m(V_i - K_i)^+] \tag{B44}$$

where $m = \exp\{-\gamma(\pi + \frac{1}{2}\sigma_I^2 + \epsilon_C)\}$. To get from (B42) to (B43), set initial wealth $W_0 = 1$ and invoke the equilibrium condition $\pi_i^E = \pi_i^D = 1$ for all i. Note that $u'(x) = x^{-\gamma}$, and that the aggregate payoff of the market is as shown in (17).

We can show that the stochastic discount factor, m, also provides equilibrium prices for both the bonds and the risk-free asset in the economy following the same procedure as above.

□

Proof of Proposition 6

To prove Proposition 6 it is sufficient to show that:

$$\left|\lim_{K_i \to 0} \frac{\partial}{\partial K_i} E[R_i^E]\right| > \left|\lim_{K_i \to 0} \frac{\partial}{\partial K_i} E[R_i^D]\right| \geq 0$$

for $\gamma\sigma_C^2 \neq \theta\delta$.

First, note that:

$$\frac{\partial}{\partial K_i} E[R_i^E] = \frac{1}{P_i^E} \frac{\partial}{\partial K_i} E[(V_i - K_i)^+] - \frac{1}{P_i^E} E[R_i^E] \frac{\partial}{\partial K_i} P_i^E \tag{B45}$$

$$= \frac{1}{P_i^E} \left(e^{-y^f} E[R_i^E] \Phi(DD_i - \frac{\gamma \sigma_C^2 - \theta \delta}{\sigma_V}) - \Phi(DD_i) \right) \tag{B46}$$

$$\Rightarrow \lim_{K_i \to 0} \frac{\partial}{\partial K_i} E[R_i^E] = \frac{1}{P_i^V} \left(e^{-y^f} E[R_i^V] - 1 \right) \tag{B47}$$

$$= \frac{1}{P_i^V} \left(\exp\{\gamma \sigma_V^2 - \theta \delta\} - 1 \right) \begin{cases} < 0 & \text{for } \theta > \theta^* \wedge \delta > 0 \\ = 0 & \text{for } \theta = \theta^* \\ > 0 & \text{otherwise} \end{cases} \tag{B48}$$

where the last line is given by Proposition 1.

Next, we look at the sensitivity of expected bond returns in the limit:

$$\frac{\partial}{\partial K_i} E[R_i^D] = \frac{1}{P_i^D} \frac{\partial}{\partial K_i} E[\min(V_i, K_i)] - \frac{1}{P_i^D} E[R_i^D] \frac{\partial}{\partial K_i} P_i^D \tag{B49}$$

$$= \frac{1}{P_i^D} \left(\Phi(DD_i) - e^{-y^f} E[R_i^D] \Phi(DD_i - \frac{\gamma \sigma_C^2 - \theta \delta}{\sigma_V}) \right) \tag{B50}$$

$$\Rightarrow \lim_{K_i \to 0} \frac{\partial}{\partial K_i} E[R_i^D] = 0 \tag{B51}$$

Therefore, for low enough K_i, the expected return on equities is more sensitive to changes in risk than the expected returns on bonds:

$$\left| \frac{\partial}{\partial K_i} E[R_i^E] \right| \geq \left| \frac{\partial}{\partial K_i} E[R_i^D] \right| \geq 0$$

□