Why Does the Term Structure of Credit Spreads Predict Equity Returns?*

Patrick Augustin,[†] Jan Ericsson,[‡] Haohua Xu[§]

March 17, 2025

Abstract

Previous literature finds conflicting evidence on the predictability between the equity and credit markets by only focusing on the level of the credit spread. This inference omits significant information embedded in the credit spread term structure. We revisit this predictability using the credit spread term structure and find that the term structure of the credit spreads significantly predicts equity returns conditional on the credit spread level. A stylized structural credit risk framework demonstrates that the shape of the term structure contains useful information on the leverage and asset volatility of the firm. These components are associated with the equity beta and asset risk premium embedded in the equity risk premium.

JEL classification: G12, G13

*

[†] Desautels Faculty of Management, McGill University; patrick.augustin@mcgill.ca.
[‡] Desautels Faculty of Management, McGill University; jan.ericsson@mcgill.ca.
[§] Desautels Faculty of Management, McGill University; haohua.xu@mcgill.ca.

1 Introduction

Firms finance their operations in both equity and credit markets, where prices are formed based on what is known about the firms' fundamentals. In a friction-free world, such as in the Merton (1974) model, both markets simultaneously aggregate available information, and each market is equally informative about the other. However, in the presence of frictions, this may no longer be the case.

A significant body of work has emerged discussing the degree of integration between the two markets and how this may lead to differences in information revelation across them (e.g. Acharya and Johnson, 2007; Hilscher, Pollet, and Wilson, 2015, Lee, Naranjo, and Velioglu (2018)). [1] The typical study in this literature takes as starting point the level of credit spreads as a representative pricing metric. An important recent exception is Han, Subrahmanyam, and Zhou (2017) who argue that there is more information in the term structure of CDS spreads than just the level. They find that the slope is a predictor of stock returns over a 6-month horizon and attribute their finding to arbitrage costs, providing support for imperfect integration between equity and credit markets.

We contribute to this literature by showing that the information embedded in the slope, taken together with the CDS spread, can be better understood by viewing it through the lens of a structural credit model without frictions. In the Merton model, a firm's debt can yield a given credit spread by being either a high unlevered risk firm with low leverage or a low unlevered risk firm with high leverage. The slope of the term structure of credit spreads provides information that allows us to identify which.

A basic intuition in the Merton model is that a firm which is in immediate distress but would be in better shape in the longer term conditional on surviving a current crisis, has a downward sloping term structure of credit spreads. Let's call this a type I firm. Conversely, a firm which is at negligible risk in the short term may see its risk increase in the future. Such a firm (type II) will exhibit a positive slope. Extending this basic intuition, we prove that for a given level of credit spread at a fixed intermediate maturity, the low slope type I firm is one

[1] Other recent work measuring the degree of integration between the two markets include.

with high leverage and low volatility. The type II firm with higher slope corresponds to one where the leverage is relatively low and volatility higher. Taken together this means that in a pool of firms with similar default risk, an increase in the slope signals a shift from a type I firm to a type II firm.

This matters as we are able to show that, in our model, equity risk premia depend both on the amount of default risk and the slope of the credit spread term structure. The risk premium is the product of the Sharpe ratio, the unlevered asset volatility, and a leverage adjustment. We show that within a group of firms with high default risk, type II (higher slope) firms are expected to have lower ex ante excess returns than type I firms. In contrast, for low default risk firms, type II firms have higher ex ante excess returns. Hence the credit spread slope predicts lower returns if default risk is high and higher returns when default risk is low.

Motivated by this insight, we revisit the predictability of equity returns using credit market data while focusing on both the level and slope of the term structure of the credit spreads. We find that the credit spread slope, defined as 10-year credit spread minus 1-year credit spread, has stronger predictive power than the credit spread level in the cross-section of the equity returns, consistent with the findings in Han, Subrahmanyam, and Zhou (2017).

To better understand the interplay between level and slope, we first analyze stock portfolios double-sorted on these two metrics. For low spread firms, a higher slope is associated with higher returns, whereas the opposite is true for high spread firms, consistent with our theoretical prediction.

We provide further evidence by conducting a panel regression projecting future equity returns on the current CDS slope, its interaction with the spread level, as well as high / low CDS spread indicators. We find that the CDS slope has a significant positive (negative) effect on the future equity returns conditional on low (high) credit spread levels. This finding is robust to introducing firm and time fixed effects, a broad variety of controls, alternative measures of the slope, and excluding the 2008-2009 financial crisis period. Our findings are not likely to be driven by a growth effect, liquidity risk, downside risk, and short selling.

Our model-based prediction does not require the assumption of any information frictions.

To see whether market imperfections could play a role nonetheless, we check whether our documented predictability is generated by informed trading in the CDS market. First, we repeat the double-sort analysis while dropping firms that are less transparent, as measured for example by low CDS market depth, high idiosyncratic risk, small size, low institutional ownership, and low analyst coverage, all indicators of a higher propensity for informed trading. Second, we repeat the panel regression while controlling for the firm's transparency proxies. We find consistent significant double-sort and panel regression results, indicating the predictability between the CDS term structure and equity return is not driven by an informed trading channel in the CDS market.

We perform a series of further robustness tests. We consider alternative specifications of our empirical slope proxy. Additionally, we show that our predictability is not derived from any industry-specific effects embedded in the CDS term structure. Furthermore, the predictability between the credit spread term structure and equity returns is not a CDS market specific pattern. The same conclusions hold in corporate bond data.

In the context of the Merton (1974) model, we prove analytically that for a constant credit spread level, a steeper term structure indicates a higher asset volatility but lower leverage. In addition we sudy the theoretical link between equity risk premia and the credit spread term structure. More specifically, we decompose the equity risk premium into an equity beta component and an asset risk premium component. We show that these two components influence the equity risk differently depending on whether we consider firms with high or low credit quality.[2]

On the one hand, the equity risk premium of a high credit quality firm is mainly driven by the asset risk premium. Such a firm is far from default, has an equity value similar to the asset value and an equity beta likely closer to its asset beta. As a result, the equity risk premium is mainly driven by the asset risk premium. Since the asset risk premium is closely related to the asset volatility and a high credit spread slope indicates a high asset volatility, the credit spread slope positively predicts the equity returns.

[2]We also consider an alternative choice of structural credit model, the Leland (1994) framework, for which we show that our predictions are the same.

On the other hand, the equity risk premium of a low credit quality firm is mainly driven by its equity beta. This firm is likely closer to default, have an equity value much lower than its asset value and an equity beta much higher than one. In these circumstances, the equity beta plays a bigger role than the asset risk premium.

For a given The higher (lower) the leverage (asset volatility) is, the smaller the equity value and the larger the equity beta is. Since low credit spread slope corresponds to high (low) leverage (volatility), the credit spread slope negatively predicts the equity returns.

To further justify that the economic channel in the model is responsible for the different predictability between CDS slope and equity returns conditional on different types of firms, we simulate the Leland (1994) model to generate panel data. By replicating the same double-sort and panel regression exercise as the empirical analysis, we find qualitatively similar results as the results produced by the market data. This again supports our conjecture that the predictive power of the CDS slope arises because the CDS slope reflects the additional information on the leverage and asset volatility.

Our work contributes to the debate on the predictability between equity and credit markets, by showing the predictive relations between the credit spread term structure and equity returns, conditional on high and low credit spread level, both empirically and in a rational theoretical framework. It highlights the importance of focusing on the credit spread term structure in studying the relation between these two markets.

This paper is organized as follows. Section 2 provides a literature review. Section 3 presents a preliminary analysis of the predictability between the equity and credit markets. Section 4 documents the empirical evidence on the predictive power of credit spread term structure conditional on the credit spread level. In section 6, we provide a theoretical framework in understanding the information content of the credit spread term structure and how it is related to the equity risk premium. Section 7 concludes.

2 Literature

This paper is related to the literature on cross-sectional stock return predictability. On the one hand, several papers argue that the predictive power of firm characteristics, such as size, book-to-market ratio, and momentum, can be reconciled with a rational expectations framework (e.g. Fama and French, 1992; Fama and French, 1996; Jagannathan and Wang, 1996; Zhang, 2005). On the other hand, many studies explain the stock predictability based on investor irrationality or market imperfections (e.g. Shleifer and Vishny, 1997; Jegadeesh and Titman, 1993; Lakonishok, Shleifer, and Vishny, 1994; Nagel, 2005). This paper aligns with the first stream of literature in understanding the equity risk premium through a credit risk model without frictions.

This paper also relates to the literature on the links between different corporate contingent claims. For example, several papers study the integration between equity and debt and markets (e.g. Choi and Kim, 2018; Lewis, 2019; Sandulescu, 2020), as well as equity and CDS (e.g. Kapadia and Pu, 2012; Augustin, Jiao, Sarkissian, and Schill, 2019). Some studies examine the relation between the equity derivatives and credit derivatives (e.g. Carr and Wu, 2011; Culp, Nozawa, and Veronesi, 2018; Collin-Dufresne, Junge, and Trolle (2020); Xu (2021)).

Within this literature, there is a debate on the lead-lag relation between the equity and credit markets. Acharya and Johnson (2007) find that the CDS market leads the equity market due to informed trading in the CDS market. Ni and Pan (2020) also find that the credit market predicts the equity market because of equity short selling constraints. In contrast, Hilscher, Pollet, and Wilson (2015) provide evidence that the equity market predicts the CDS market and the informed trader prefers the equity market because of lower transaction costs. Norden and Weber (2009) provide further statistical evidence that the equity market leads the credit market. More recently, Lee, Naranjo, and Velioglu (2018) finds that the equity market leads the CDS market unconditionally. However, the CDS market predicts the equity market when the credit event takes place.

Most of these studies focus on the credit spread level. Given the recent findings of Han, Subrahmanyam, and Zhou (2017), this omits significant information embedded in the credit spread term structure, which may be helpful in predicting equity returns. Our paper presents both theoretical and empirical evidence to show that the credit spread term structure can reflect different combinations of asset volatility and default boundary, even though these combinations produce the same credit spread level. Table A1 summarizes the main differences between our and the existing contributions.

Many studies have shown that the term structure of different asset classes, such as currencies, equity and dividend derivatives, inflation, U.S. government bonds, and volatility, contains valuable information on the pricing of risk (e.g. Cochrane and Piazzesi, 2005; Binsbergen, Brandt, and Koijen, 2012; Zviadadze, 2017; Fleckenstein, Longstaff, and Lustig, 2017; Augustin, 2018; Gruber, Tebaldi, and Trojani, 2020). This paper contributes to this literature by showing that the term structure of credit spreads contains important information on the equity risk premium.

Our paper is mostly related to Han, Subrahmanyam, and Zhou (2017), who also study the predictability of the CDS term structure for equity returns. However, they focus on the slow information diffusion channel in driving the predictability. Furthermore, they document an unconditional relation between the CDS slope and equity returns. Complementing their study, we present a conditional relation between the CDS slope and equity return, which arises based on the by now classic Leland (1994) framework rather than frictions.

This paper is also related to the literature on structural credit models. Dating back to the seminal work of Merton (1974), a number of papers develop structure frameworks in jointly pricing the equity and credit claims, as well as corporate decision making (e.g. Black and Cox, 1976; Leland, 1994; Leland, 1998; Goldstein, Nengjiu, and Leland, 2001; Du, Elkamhi, and Ericsson, 2019). In this paper, we adopt the Leland (1994) framework in decomposing the equity risk premium and the credit spread slope to understand the interplay between these components.

3 Preliminary analysis

In this section, we conduct a preliminary analysis to understand the predictive relation between the equity and credit markets. First, we describe the data. Second, we study this predictability between equity and credit by relating both the credit spread level and term structure to equity returns.

3.1 Data

We obtain CDS quotes from MARKIT. Our sample period covers the period from January 2001 to March 2018. We restrict our sample to consist only of US corporate entities and non government sectors. We consider only US dollar-denominated senior unsercured tier CDS. Furthermore we drop any observations with missing values of the CDS for the following maturities: 1, 2, 3, 5, 7, and 10 years.

We obtain monthly stock price data from CRSP with share code 10 or 11. We also include delisting returns. We manually match the CRSP "PERMCO" and MARKIT "REDCODE" company identifiers by checking the company names of the two datasets.[3] We also manually filter out the matchings such as parent-subsidiary matching. For example, if the AT&T Inc. matches with AT&T Corp, we drop such matchings.

Table 1 documents the sample cross-sectional descriptive statistics.[4] Our sample contains 759 firms with 76,517 firm-month observations from January 2001 to March 2018. The cross-sectional average 5-year CDS spread is 250 bps and the average of the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, is 60 bps. The median firm in the sample has a leverage of 30.2%, equity volatility of 30%, log market capitalization of 8.7, book-to-market of 0.6, and BBB rating. This is consistent with the total Compustat sample median documented in the previous literature (e.g. Feldhütter and Schaefer, 2018), indicating that our sample is fairly representative of the Compustat universe.

[3] When a PERMCO has multiple PERMNO a day, we choose the stock (PERMNO) with the largest market capitalization.

[4] We first compute the unconditional averages of the variables for each firm. We then generate the cross-sectional summary statistics.

3.2 The predictability between equity and credit markets

In this section, we revisit the predictability between the credit and equity markets, relating it to the the credit spread term structure in addition to merely the spread level. As a first step, we examine the unconditional relation between credit spread slopes, levels[5] and future equity returns.

To do so, we carry out simple portfolio sorts. We first sort the stocks into deciles based on the CDS level and slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Second, for each decile, we compute the equally-weighted one month ahead equity return. Lastly, we compute the low slope - high slope long-short portfolio return.

Table 2 reports the results. We find that higher credit spread level (slope) deciles have higher (lower) equity future returns than lower credit spread level (slope) deciles on average. The low - high portfolio return is not significant for the portfolio sorted by CDS spread level, but significantly positive at the 10% confidence level for the portfolio sorted by CDS spread slope, using Newey-West standard errors. We thus provide preliminary evidence that the credit spread slope negatively predicts equity returns, consistent with the findings in Han, Subrahmanyam, and Zhou (2017). Furthermore, the credit spread slope exhibits stronger predictive power than the credit spread level.

As an additional test, we perform the following panel regression, projecting the one-month ahead equity returns on the CDS spread level and slope.

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \beta Var_{i,t} + Y_{i,t}'\beta_Y + \epsilon_{i,t} \tag{1}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one-month ahead return, Var_i denotes either the CDS spread level, defined as 5-year CDS spreads, or slope, defined as 10-year CDS spreads minus 1-year CDS spreads, α_i denotes the firm fixed effect, γ_t denotes the year-month or quarter fixed

[5] Although the CDS spread contains illiquidity component, Bongaerts, De Jong, and Driessen (2011) find that such component is economically insignificant. Hence, we omit such effect for simplicity and introduce CDS depth as a control variable for regressions. Nevertheless, the illiquidity might impact the long and short term CDS spreads differently. It will be interesting to exclude the illiquidity noise embedded in the CDS spread level and slope in a, e.g. reduced form manner, and to use this clean measure to study the predictability between the equity and credit market. We leave this for future work.

effect, and Y_i denotes the firm specific control variables. The firm specific controls include the firm's leverage ratio, log market capitalization, annualized stock volatility computed using the previous month daily stock returns, rating, and daily stock return.

Table 3 reports the regression results. Columns (2) and (4) report the results of the same regression by substituting the year-month fixed effect into quarter fixed effect with additional macroeconomic controls. The macroeconomic control variables are the CBOE VIX index, 10-the year treasury yield, the yield curve slope (defined as 10-year yield minus 2-year yield), the default spread, and the TED spread.

The CDS spread level is not significant in predicting equity returns while the CDS spread slope is significant at the 10% confidence level for both regression specifications. Furthermore, the encompassing regressions (5) and (6) show that the predictive effect of the credit spread slope survives after controlling for the credit spread level. This suggests that the predictability between the credit and equity market improves by incorporating term structure information for CDS spreads.

4 Empirical results

To further establish that the CDS slope contains information predictive of equity returns, we perform a double sort exercise and panel regression analysis to study the predictive power of the slope on the equity returns conditional on the spread level. We also perform several robustness checks.

4.1 Stock portfolios sorted on CDS levels and slopes

To examine the relation between CDS slopes and future equity returns conditional on CDS levels, we perform a bivariate dependent-sort portfolio analysis (Engle, Bali, and Murray, 2016).

At each month, we first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, into five quintiles. Third, for each group, we compute equally-weighted one-month ahead portfolio's returns. Fourth, within each CDS tercile, we compute the low slope quintile minus high slope quintile portfolio return. Finally, we calculate time series averages of these portfolio returns and compute the t-statistics using Newey-West standard errors.

Figure 2 presents a visual summary of the double sort exercise and Table 4 reports the statistical results. Visually, we see that conditional on low (high) credit spread level, the future equity returns are increasing (decreasing) with the CDS slope. These patterns are statistically significant. The long short portfolio, defined as low slope portfolio minus high slope portfoilo, earns significantly negative (positive) returns, for the low (high) CDS spread level tercile. This evidence suggests that the credit spread term structure contains additional information beyond that in the credit spread level. The sign of the predictability between the CDS slope and equity returns are different conditional on the credit spread level.

To further examine this pattern, we perform a panel regression, projecting the future equity returns on the CDS slope and its interaction with credit spread levels. The regression specification is:

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t \times Slope_t + \beta_l Level_t + Y_{i,t}' \beta_Y + \epsilon_{i,t} \tag{2}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ in 3 different forms: (i) a dummy taking on the value one if the spread is higher (lower) that the average and zero otherwise, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), (ii) a dummy taking on the value one if the spread is higher (lower) than 500 (30) basis points or zero otherwise, $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$), and (iii) the raw 5 year CDS spread.

The coefficients β_u and β_c denote the unconditional and conditional effects of the CDS slope, respectively. The constant α_i denotes the firm fixed effect, γ_t the year-month fixed effect, and the variable Y_i represents the firm-specific control variables. These controls are the leverage ratio, log market capitalization, annualized stock volatility, daily stock return, and 5-year CDS spreads.[6]

Table 5 reports the regression results. The coefficients of $Level_t \times Slope_t$ under the 3 different specifications of $Level_t$ are significant and differ in sign conditional on the spread level. Specifically, the coefficients of $D_{highCDS,avg} \times Slope$ ($D_{lowCDS,avg} \times Slope$), $D_{highCDS,600bp} \times Slope$ ($D_{lowCDS,30bp} \times Slope$), and $CDS_{5y} \times Slope$ are significantly negative (positive). This suggests that conditional on high (low) credit spreads, the predictive effect of the CDS slope becomes more negative (positive). Furthermore, $\beta_u + \beta_c$ is positive (negative) for firms with low (high) CDS spread level. This again supports that the CDS slope positively (negatively) predicts the equity returns for firms with low (high) CDS spread level.

In sum, we find evidence supportive of previous work documenting that the CDS slope has additional predictive power on the equity returns. Our contribution is to show that the slope predicts returns differently depending on credit quality. It positively predicts equity returns for high credit quality firms but negatively predicts equity returns for low credit quality firms. Not surprisingly, due to the opposite signs of predictability in these two situations, we find a weak unconditional relationship between the CDS slope and equity returns (section 3).

5 Robustness

Given such interesting patterns in the data, we investigate several economic mechanisms which might give rise to such results.

5.1 Growth effect

To begin with, CDS spreads are affected by variance risk, which can be influenced by growth opportunities of a firm. Intuitively speaking, the more idiosyncratic the firm is, the lower the credit spread slope is (Augustin, 2018). A firm that possesses many growth opportunities is

[6] The annualized stock volatility is calculated using the previous month's daily stock returns. Idiosyncratic risk is computed as the fraction of stock idiosyncratic volatility of the total stock volatility based on the Fama-French 3 factor model.

usually more idiosyncratic and hence subject to lower equity risk premium. This can create a positive relation between the credit spread slope and equity future returns for low credit spread level firms. To account for such channel, we incorporate the idiosyncratic risk variable and the firm size[7] as control variables to proxy growth opportunities. The relation between the CDS slope and equity return still remains.

5.2 Forward-looking information

Another potential channel for the result is that the CDS slope contains forward-looking information about the downside risk of the equity market. Furthermore, equity returns can be skewed based on its P-measure. This might also show up in the CDS slope information content. To control these channels, we first incorporate a time fixed effect, which will absorb any market risk. We then incorporate a number of firm specific controls such as leverage, equity volatility, size, etc, which proxy the equity P-distribution property. Our result is robust given such controls.

5.3 Liquidity and financial intermediary risk

Might illiquidity be an alternative explanation for our findings? For instance, it has been shown that CDS spreads provide compensation for illiquidity (e.g. Bongaerts, De Jong, and Driessen, 2011). This illiquidity component could be related to financial health of financial intermediaries (e.g. Kondor and Vayanos, 2019), who are the marginal investors in a variety of markets (e.g. He, Kelly, and Manela, 2017).Given that financial intermediary risk is positively related to the expected equity returns, it provides a plausible mechanism for the CDS slope's predictability. We rule out this concern by introducing time fixed effects to absorb the systematic variation caused by the financial intermediary.

Furthermore, the term structure of the illiquidity component embedded in the CDS spreads may also contain information that can help predict equity returns. To address these concerns, we incorporate CDS depth as a control variable. If predictability were mainly driven by the

[7] since a small firm is likely to have more growth opportunities.

liquidity factor, the predictive power of the CDS slope should be stronger when the illiquidity component is larger. However, our results remain statistically significant after controlling for CDS illiquidity.[8]

5.4 Short-selling and the financial crisis

Furthermore, these results are not driven by the financial crisis period. During the financial crisis, the Securities and Exchange Commission (SEC) issued an emergency ban on short sale for all financial stocks. The literature documents that this can induce the informed traders choosing the derivatives market to exercise their trades (Ni and Pan, 2020, etc.), resulting in CDS slope predicting equity returns. We find that excluding the financial crisis from our sample does not change our findings materially and thus that the predictive patterns found for the slope are not likely to be driven by short sale constraints.

5.5 Different slope definitions

The computation of credit spread slope is crucially dependent on our selection of the maturity. To examine whether the empirical results are robust across different credit spread slope definitions, we conduct the double-sort and panel regression exercises using the CDS slope defined as 10-year CDS spread minus 2-year CDS spread, and 7-year CDS spread minus 2-year CDS spread.

Table 6 reports the double-sort results and Table 7 reports the results of the panel regression following Equation (2), based on the different credit spread slope definition. We find robust results that the CDS slope positively (negatively) predicts the equity returns conditional on firms with low (high) credit spread level. The results are highly significant across different slope definitions. This suggests that the predictive relation between the CDS slope and equity returns is not affected by the credit spread slope definition.

[8] In the later section, we drop the illiquid sample to perform the double sort analysis, our result is still significant.

5.6 The impact of informed trading

Acharya and Johnson (2007) shows that the CDS market is more informative than the equity market, since the banks acquire non-public information through the lending relationship with debtors and use it in the trading of CDSs. Han, Subrahmanyam, and Zhou (2017) documents that the predictive power of the CDS slope on the equity market can also come from the informed trading behaviour in the CDS market. In particular, they show that the predictive effect of the slope are stronger conditional on the firms with low visibility.

To examine whether the predictive power of the slope conditional on different credit spread levels is purely driven by the informed trading channel, we first perform the double sort exercise by removing the firms that are more likely to be subjected to informed trading. We do so by first dropping firms with average transparency proxy ranked among the bottom quarter. These transparency proxies include CDS depth, idiosyncratic risk, institutional ownership, analyst coverage, and size. Second, we repeat the double sort exercise as documented in the previous section.[9]

Table 8 reports the result. Except the low CDS spread level group controlling for low institutional ownership, the long short portfolio returns in all other groups across other transparency controls are statistically significant. All long short portfolio returns' signs are consistent with previous findings.

As an alternative test, we perform the same regression following Equation (2) with an additional term by interacting the CDS slope with the firm's transparency proxies, such as the firm's CDS depth, idiosyncratic risk (Idiosyn), institutional ownership (IO), analyst coverage (# Analyst), and market capitalization

Table 9 documents the regression results. The coefficients of $D_{highCDS,600bp} \times Slope$, and $CDS_{5y} \times Slope$ are significantly negative across regressions with different firm's transparency proxies. The coefficient of $D_{lowCDS,30bp} \times Slope$ is significantly positive. This indicates that controlling for the informed trading proxies, the CDS slope still has significantly more negative (positive) predictive effect on the equity returns, conditional on credit spread levels.

[9] We first sort the stocks into quartiles based on the CDS spread level. We then sort the stocks into terciles based on the CDS slope within each quartile. Other sorting yields qualitatively similar results.

5.7 The impact of industry effect

The CDS slope might contain not only the firm fundamental information content, but also industry-wide effects, since an industry wide shock - related, for example, to technology, collateral, supply chain, Covid led demand shocks etc. - can have diffused effects on all firms. These industry-wide effects can also impact the equity risk premium. Hence, it is possible that the predictability of the equity returns comes from the industry wide information content embedded in the CDS slope.

To rule out such explanation, we re-perform Regression (2) by introducing an additional industry fixed effect, where the industry definitions are based on Fama-French definition. Table 10 reports the results. All interaction variable coefficients have the same signs and similar magnitude as those in Table 5. Furthermore, all interaction variables coefficients are significant at 5% confidence level. Therefore, industry-wide effects are not likely to be the main drivers of the predictive patterns between the CDS slope and equity returns.

5.8 Corporate bond market

To examine whether the predictive relation between the credit spread slope and equity returns only exists in the CDS market, we also perform the main analysis using the corporate bond data.

We obtain the corporate bond yield data from WRDS Bond Returns. Following Han, Subrahmanyam, and Zhou (2017), we remove callable, puttable, convertible, sinking funds, and floater bonds. We also drop non-coupon bonds and bonds with time-to-maturity under one year since they are illiquid. Moreover, we group the bonds by maturity into 3 bins, namely short term, median term, long term bonds, respectively. We compute the short term yield as the average bond yield with maturity smaller than 4 years, median term yield as the average bond yield with maturity greater than 4 years but smaller than 9 years, and the long term yield as the average bond yield with maturity greater than 9 years.

Table A2 documents the descriptive statistics. After matching the bond data with our original sample, we are left with 6,520 observations with 130 firms that have non-missing short term, median term, and long term yield. The median firm in the sample has a leverage of 36.5%, equity volatility of 0.28, log market capitalization of 9.7, book-to-market of 0.7, and A rating. Compared to the original sample, the bond sample is biased towards high credit quality firms. Figure A1 plots the time series of the aggregate 5-year CDS spreads and bond yields for different terms. The pairwise correlation between the bond yields and the CDS spread in this sample are approximately 90%.

We conduct the same analysis as in Section 4 based on our bond sample. Table 11 documents the double-sort results. Due to data limitation, we sort the firms into tercile rather than quintile based on the slope. Qualitatively, the implication is consistent with the empirical results in the previous sections. The portfolio returns within the low yield group is increasing with slope but decreasing with slope in the high yield group. The long short slope portfolio return is significant with the same sign as our previous empirical findings.

Table 12 reports the panel regression results following Equation (2). The signs of the β_c are all consistent with our previous findings, regardless of different proxies for credit spread level. The β_c coefficients are mostly significant and all of them are highly significant once we remove the financial crisis period. This is likely due to the external factors, such as constrained intermediaries, distort the bond price valuation and weakens their predictive effects on the equity returns (Duffie, 2010). Moreover, since bond data is much more illiquid compared to the CDS data, one might expect a weaker relationship between the bond yield slope and future equity returns due to illiquidity noise (Blanco, Brennan, and Marsh, 2005). Nevetheless, for the most part, our results suggest that term structure from the bond yield also positively (negatively) predicts the equity return for good (bad) credit quality firms.

6 Theory

In this section, we work within a structural credit risk framework to understand the economic mechanism behind the predictability between the credit spread term structure and equity returns. First, we provide analytical findings on the predictability under the Merton (1974) model. These are robust to the choice of model. Second, we conduct numerical analysis based on the analytical findings to relate the slope to returns. Finally, we simulate a panel data based on the Leland (1994) model and perform the double sort and panel regression exercises we relied on in Section 4.

6.1 The Merton (1974) model

According to the Merton model, the evolution of the firm value is described by a Geometric Brownian Motion:

$$\frac{dV(t)}{V(t)} = \mu dt + \sigma dB(t) \tag{3}$$

The firm issues zero coupon debt with maturity T. The firm defaults when the asset value V_T falls below the default boundary V_B at time T, where the default boundary V_B is assumed to be the debt face value. If the firm does not default, the equity holder receives $V_T - V_B$ at time T. Otherwise, she receives nothing. Hence, the equity has a payoff equivalent to a call option written on the firm's asset value. Based on the Black-Scholes formula, we have

$$E(t) = V(t)N(d_1) - V_B e^{-rT} N(d_2), \tag{4}$$

where

$$\begin{aligned} d_1 &= \frac{\log\left(\frac{V(t)}{V_B}\right) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}} \\ d_2 &= d_1 - \sigma\sqrt{T}. \end{aligned} \tag{5}$$

In the Merton model, the market price of risk for any security that derives its value from the assets is a constant, which we will denote ξ. From the equity dynamics we obtain by Itô's lemma we know that the instantaneous equity return volatility is

$$\sigma_E = \frac{\partial E(t)}{\partial V(t)} \frac{V(t)}{E(t)}, \tag{6}$$

and as a result

$$ERP(t) = \frac{\partial E(t)}{\partial V(t)} \frac{V(t)}{E(t)} \sigma \xi. \tag{7}$$

Next, we turn to the credit spread. Under the assumption that the creditor obtains a fraction R of the price of the equivalent maturity Treasury at default ("Recovery of Treasury"), the price of a zero coupon bond with maturity τ is

$$\begin{aligned} e^{-yT} &= e^{-rT}(\pi^Q(t) \cdot R + 1 - \pi^Q(t)) \\ e^{-(y-r)T} &= 1 - \pi^Q(t) \cdot (1-R) \\ y - r &= -\frac{1}{T}\log(1 - \pi^Q(t) \cdot (1-R)) \\ y - r &\approx \frac{\pi^Q(t) \cdot (1-R)}{T}, \end{aligned} \tag{8}$$

where π^Q denotes the risk neutral default probability, which in turn can be written:

$$\pi^Q(t) = N(-d_2) = N\left(\frac{\log\left(\frac{V_B}{V(t)}\right) - \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}\right) \tag{9}$$

based on the Merton model.

The last approximation in Equation (8) is due to $\log(1+x) \approx x$ when x is small.[10] For the purpose of analyzing the slope, suppose $R = 0$.[11] Therefore, the credit spread slope can be expressed as

$$\begin{aligned} slope &= \frac{\pi^Q(t)}{T_2} - \frac{\pi^Q(t)}{T_1} \\ &= \frac{1}{T_2}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right) - \left(r - \frac{1}{2}\sigma^2\right)T_2}{\sigma\sqrt{T_2}}\right) - \frac{1}{T_1}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right) - \left(r - \frac{1}{2}\sigma^2\right)T_1}{\sigma\sqrt{T_1}}\right), \end{aligned} \tag{10}$$

where $T_2 > T_1$.

In the Merton model, leverage and asset volatility are the key drivers of credit risk (Collin-Dufresne, Goldstein, and Martin, 2001; Ericsson, Jacobs, and Oviedo, 2009). However, the credit spread level by itself is not sufficient to separately identify these two quantities. In the following theorem, we show that by also considering the credit spread slope, one can identify

[10]Chang, D'Avernas, and Eisfeldt (2021) also use this formula to approximate credit spread.
[11]Keeping a constant recovery rate given default will not affect the results below.

these factors cross-sectionally.

Theorem 1. *Define the credit spread slope to be T_2-year credit spread minus T_1-year credit spread with $T_2 > T_1$. Given a constant credit spread level at T-year maturity, where $T_1 \leqslant T \leqslant T_2$, the asset volatility is increasing with the slope and the default boundary is decreasing with the slope.*

The proof can be found in Appendix C.

Firms that have similar credit spread levels can have very different underlying asset dynamics. Some firms could have high asset volatility but low leverage while other firms could have high leverage and low asset volatility. Theorem 1 shows that the term structure of credit spreads can pinpoint the relative magnitude of the leverage and asset volatility across different firms with the same credit spread level. For a given credit spread level, as we steepen the term structure around this credit spread, the corresponding firm will tend to have higher asset volatility but lower leverage.

Intuitively, this is because short term credit spreads are more sensitive to leverage while long term credit spreads are more sensitive to asset volatility. Based on Merton's insight, since the credit spread is a function of a put option written on the firm's assets, one can understand the determinants of long or short term credit spreads by considering the sensitivities of long and short term put options.

Consider a very short term put option, say one day to expiration. The value of this option is largely determined by its moneyness. If the option is in-the-money it is likely to remain there, whereas if it is out-of-the-money it is unlikely to make it into the money. The volatility is secondary as it does not have much time to play out. Translating this into credit spreads, since in the Merton model, the strike price is the default boundary V_B, the short term put and hence credit spread is mainly driven by this boundary or, equivalently, leverage.

On the other hand, for a longer term option, what matters is the asset value's potential to grow beyond the default boundary, a growth which depends to a significant extent on the asset volatility. So long term credit spreads will be more sensitive to volatility than leverage.

[12]

Due to the different drivers of long and short term credit spreads, if we observe a steeper term structure, the asset volatility of the corresponding firm is likely to be higher and the default boundary (leverage) correspondingly lower.

Next, we discuss the joint impact of the leverage and asset volatility on the equity risk premium. According to Equation (7), the ERP can be decomposed into a leverage component $L = \left(\frac{\partial E(t)}{\partial V(t)} \frac{V(t)}{E(t)}\right)$ and an asset risk premium component ($ARP = \sigma\xi$). For a high credit quality firm, the leverage adjustment L is small, and the ERP is mainly driven by the asset risk premium, which is closely related to asset volatility. Consider the extreme case with no leverage, the default boundary is zero and the equity value equals the asset value. In this case $L = 1$ and all the variation in the ERP is driven by variation in the ARP.

Suppose now we consider a cross-section of high quality (low spread) firms. Those with a high credit slope will tend to have higher asset volatility. This higher volatility increases the ERP, dominating the negative effect of reduced leverage.

For a low credit quality (high spread) firm, L is larger and tends to dominate the influence of the asset volatility in so far as slope changes are concerned. Like the case of a lower spread firm above, for a given higher spread, an increased slope increases the asset volatility at the expense of leverage. Now, contrary to the lower spread situation discussed above, the reduced leverage dominates the effect of the increased asset volatility and the ERP is reduced.

In summary then, Theorem 1, tells us that conditional on the same credit spread level, a high credit slope corresponds to high asset volatility and low leverage. For good (bad) credit quality firms, this translates to a positive (negative) relationship between the credit spread slope and ERP, consistent with our empirical findings.

[12] The Merton model could be restrictive due to the assumption that default happens only at maturity. As a robustness exercise, we consider the Leland (1994) model, where default can happen any time before a certain maturity and show numerically that the same intuition obtains.

6.2 Numerical analysis

In this section, we provide comparative statics relating to changes in the credit spread slope. First, we fix the 5-year credit spread level and vary the credit spread slope, defined as 10-year spread minus 1-year spread. Second, for each level and slope combination, we solve for the asset volatility and default boundary of the firm based on the Merton model. Finally, we plot the leverage, asset volatility, and ERP evolution against the slope.

We perform this analysis for both high and low credit quality firms. The parameters for our comparative study are listed in Table 13. We fix the credit spread level for high and low credit quality firms to be 40 and 300 bps, respectively.[13] We set the firm value to be 100, and risk free rate to be two percent. In addition, we set the Sharpe ratio for all firms to be 0.2 (see Chen, Collin-Dufresne, and Goldstein (2009)). Moreover, we set the loss-given-default to be 0.5 regardless of credit quality.[14] Since our sample median credit spread slope is 70 bps, we vary slope between 60 to 80 bps. To compute the equity risk premium, we set the maturity to be 5 years in the Merton model.

Figure 3 reports the comparative statics result. Consistent with Theorem 1, high credit spread slope corresponds to low (high) leverage (asset volatility). Based on our parametrization, the leverage ranges between 0.15 to 0.35 for the good credit quality firm while it ranges between 0.51 to 0.53 for bad credit quality firms. In addition, the asset volatility ranges between 0.25 to 0.4 for good credit quality firms but 0.31 to 0.33 for bad credit quality firms. Therefore, ERP is mainly driven by asset volatility (leverage) for good (bad) credit quality firms. As a result, ERP is positively (negatively) related to slope.

One legitimate concern about this analysis is some restrictive assumption in the Merton model. For example, Merton assumes that the default occurs only at maturity. Furthermore, equity is not a finite maturity claim but a perpetual claim. To show that the economic mechanism still holds under a more general setting, we adopt the Leland (1994) framework.[15]

[13] These numbers are based on the median slope quintile 5-year CDS spread for both the low and high CDS tercile according to the double sort analysis in this paper.

[14] This choice is made to isolate the effect of the slope on our analysis. Empirically, the recovery rate does depend to some extent on the credit quality (rating) in the year prior to default.

[15] Appendix D describes the Leland (1994) model in details.

Figure 4 reports the comparative statics result. Without the restriction of finite equity maturity and default on maturity, the shape of the comparative statics appears virtually unchanged compared to Figure 3. Interestingly, for the same credit spread level and slope combination, the leverage becomes higher and the asset volatility becomes lower under the Leland model. This is because under the Merton model, credit risk is not as sensitive to leverage as that of the Leland model, since default occurs only at maturity. Therefore, for the same leverage and asset volatility, the term structure in the Leland model will be steeper, because the long term credit spread is much more sensitive to leverage than that in the Merton model. To generate the same slope as that in the Merton model, one needs to increase the leverage and decrease the asset volatility in the Leland model.

In sum, our comparative statics show that conditional on the same credit spread level, the slope indeed contains information about leverage and asset volatility, i.e. high slope corresponds to high asset volatility and low leverage. This information is important to understand the equity risk premium especially for the good and bad credit quality firms.

6.3 Simulation

To provide further evidence that our empirical findings can be attributed to the economic mechanism relating the credit slope and equity returns in structural credit models, we simulate a panel data based on the Leland model, and conduct our main empirical analysis on this data as in Section 4.

To simulate the data, we normalize the initial firm value to 100. We construct 900 firms with volatilities ranging between 0.2 to 0.4 and default boundaries ranging between 10 to 70.[16] We set the risk free rate to two percent, loss-given-default to 0.5, bankruptcy costs to 0.15, the tax rate to 0.15, Sharpe ratio to be 0.14.[17] According to Chen, Collin-Dufresne, and Goldstein (2009), we set the market price of risk to be 0.4. We then compute the systematic volatility and idiosyncratic volatility based on the firm's sharpe ratio and the market price of

[16] In the Leland model, for firms with a 5-year credit spread level of 700 (50) bps, given an asset volatility range from 0.2 to 0.4, the highest (lowest) default boundary is approximately 70 (10), hence our parametrization.

[17] The average sharpe ratio between good and bad credit quality firm is 0.14.

risk. Finally, we simulate 10 years of daily data based on these parameters, and aggregate the sample into monthly data.

Table A3 reports the summary statistics of the simulated data. The median 1-year, 5-year, and 10-year CDS spreads are 30, 150, and 170 bps, respectively. This is consistent with our sample as well as levels in the literature (e.g. Ericsson, Jacobs, and Oviedo, 2009). In addition, the median credit spread slope and equity returns are consistent with our sample, which are about 70 bps and two percent, respectively. However, based on firm characteristics, the simulated data are biased towards lower credit quality firms. For example, the median leverage is approximately 70% and the equity volatility is 0.6.[18]

Based on this simulated data, we perform the same double sort analysis as in Section 4. As a first step, we conduct the double sort exercise at the inception of the data to rule out any time series bias in the simulation process. We focus on understanding the risk premium patterns sorted on credit spread level and slope. Figure A2 reports the risk premium patterns. The low and high credit spread level groups yield significant positive and negative relationships between the credit spread slope and equity risk premium, respectively.

To take into account the time series dynamics, we perform the double sort exercise at each month and aggregate the monthly portfolio one-month ahead returns. Table 14 and Figure 5 report the results. We see that the credit spread slope is positively (negatively) related to the one-month ahead equity returns for the low (high) CDS level group. Quantitatively, the long short slope portfolio within these two groups is highly significant and has the same sign as those of the test conducted based on our original sample.

In addition, we run a panel regression by interacting the credit spread slope with the credit spread level as described in Section 4. Table 15 reports the regression results. When conditional on high (low) credit spread level, the conditional beta β_c is significantly negative (positive), indicating that firms with high and low credit spread levels have a distinct predictive relation between the credit spread slope and the equity returns. In addition, $\beta_u + \beta_c$ is negative

[18]Note that in our simulation, leverage is exogenous, not optimized. As a result, the sample leverage could be biased. However, we emphasize that the key for this simulation exercise is to produce a sample that contains both high and low credit quality firms, since we want to understand the predictability in these two subsets.

(positive) for firms with high (low) credit spread level, indicating that for low (high) credit quality firms, the credit spread slope negatively (positively) predicts the equity returns. This is consistent with the previous empirical evidence.

In sum, the Leland model simulated data replicates the empirical evidence. Our analysis shows that the reason the credit slope contains additional predictive power beyond the credit spread level on the equity return is that the slope helps to identify the rankings of the leverage and asset volatility factors across firms; and these factors directly relate to the equity risk premium. For high (low) credit quality firms, the ERP is mainly driven by asset volatility (leverage). Hence, the credit spread slope is a significant predictor of the equity returns conditional on the credit spread level.

7 Conclusion

There has been an ongoing debate in the literature on the predictability between the credit and equity markets. However, most of these studies focus on the credit spread level. But firms with the same credit spread level may have completely different credit spread term structures. These term structures contain additional information useful in predicting equity returns.

In this paper, we revisit this intra market predictability by focusing on the term structure of the credit spread. We find that the credit spread slope, defined as 10-year spread minus 1-year spread, significantly predicts the equity returns. More specifically, conditional on high (low) credit spread level, the credit spread slope significantly and negatively (positively) predicts the equity returns.

Structural credit models, such as Merton (1974) and Leland (1994), predict that firms with similar credit spread levels might have different combinations of asset volatility and leverage. These factors are important for us to understand the cross-sectional ranking of equity risk premia. Further, the credit spread slope can identify the ranking of these factors across different firms. We show both analytically and numerically that high credit spread slope corresponds to high asset volatility but low book leverage. Since the equity risk premium is mainly driven by the asset volatility (leverage) for high (low) credit quality firms, the slope is positively (negatively) related to the equity risk premium conditional on the same credit spread level.

References

Acharya, Viral V., and Timothy C. Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110–141.

Augustin, Patrick, 2018, The term structure of CDS spreads and sovereign credit risk, *Journal of Monetary Economics* 96, 53–76.

Augustin, Patrick, Feng Jiao, Sergei Sarkissian, and Michael J Schill, 2019, Cross-Listings and the Dynamics between Credit and Equity Returns, *Review of Financial Studies* 33, 112–154.

Binsbergen, Jules_Van, Michael Brandt, and Ralph Koijen, 2012, On the Timing and Pricing of Dividends, *American Economic Review* 102, 1596–1618.

Black, Fischer, and John C. Cox, 1976, Valuing Corporate Securities: Some Effects of Bond Indenture Provisions, *The Journal of Finance* 31, 351–367.

Blanco, Roberto, Simon Brennan, and Ian W. Marsh, 2005, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *Journal of Finance* 60, 2255–2281.

Bongaerts, Dion, Frank De Jong, and Joost Driessen, 2011, Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance* 66, 203–240.

Carr, Peter, and Liuren Wu, 2011, A simple robust link between american puts and credit protection, *Review of Financial Studies* 24, 473–505.

Chang, Huifeng, Adrien D'Avernas, and Andrea L. Eisfeldt, 2021, Bonds vs. Equities: Information for Investment, *Working Paper*.

Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein, 2009, On the relation between the credit spread puzzle and the equity premium puzzle, *Review of Financial Studies* 22, 3367–3409.

Choi, Jaewon, and Yongjun Kim, 2018, Anomalies and market (dis)integration, *Journal of Monetary Economics* 100, 16–34.

Cochrane, John H., and Monika Piazzesi, 2005, Bond risk premia, *American Economic Review* 95, 138–160.

Collin-Dufresne, Pierre, Robert S Goldstein, and J Spencer Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177–2207.

Collin-Dufresne, Pierre, Benjamin Junge, and Anders B Trolle, 2020, How integrated are credit and equity markets? Evidence from index options, .

Culp, Christopher L., Yoshio Nozawa, and Pietro Veronesi, 2018, Option-Based Credit Spreads, *American Economic Review* 108, 454–488.

Du, Du, Redouane Elkamhi, and Jan Ericsson, 2019, Time-Varying Asset Volatility and the Credit Spread Puzzle, *Journal of Finance* 74, 1841–1885.

Duffie, Darrell, 2010, Asset Price Dynamics with Slow-Moving Capital, *Journal of Finance* 65, 1237–1267.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann, 2001, Explaining the rate spread on corporate bonds, *Journal of Finance* 56, 247–277.

Engle, Robert F., Turan G. Bali, and Scott Murray, 2016, (*Empirical Asset Pricing - The Cross Section of Stock Returns*).

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo, 2009, The Determinants of Credit Default Swap Premia, *Journal of Financial and Quantitative Analysis* 44, 109–132.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *The Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Feldhütter, Peter, and Stephen M. Schaefer, 2018, The myth of the credit spread puzzle, *Review of Financial Studies* 31, 2897–2942.

Fleckenstein, Matthias, Francis A. Longstaff, and Hanno Lustig, 2017, Deflation risk, *Review of Financial Studies* 30, 2719–2760.

Goldstein, Robert, Ju Nengjiu, and Hayne Leland, 2001, An EBIT-based model of dynamic capital structure, *Journal of Business* 74, 483.

Gruber, Peter H., Claudio Tebaldi, and Fabio Trojani, 2020, The Price of the Smile and Variance Risk Premia, *Management Science*.

Han, Bing, Avanidhar Subrahmanyam, and Yi Zhou, 2017, The term structure of credit spreads, firm fundamentals, and expected stock returns, *Journal of Financial Economics* 124, 147–171.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

Hilscher, Jens, Joshua M Pollet, and Mungo Wilson, 2015, Are Credit Default Swaps a Sideshow? Evidence That Information Flows from Equity to CDS Markets, *Journal of Financial and Quantitative Analysis* 50, 543–567.

Huang, Jing-Zhi, and Ming Huang, 2012, How Much of the Corporate-Treasury Yield Spread Is Due to Credit Risk?, *Review of Asset Pricing Studies* 2, 153–202.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3–53.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65–91.

Kapadia, Nikunj, and Xiaoling Pu, 2012, Limited arbitrage between equity and credit markets, *Journal of Financial Economics* 105, 542–564.

Kondor, Péter, and Dimitri Vayanos, 2019, Liquidity Risk and the Dynamics of Arbitrage Capital, *Journal of Finance* 74, 1139–1173.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *The Journal of Finance* 49, 1541–1578.

Lee, Jongsub, Andy Naranjo, and Guner Velioglu, 2018, When do CDS spreads lead? Rating events, private entities, and firm-specific information flows, *Journal of Financial Economics* 130, 556–578.

Leland, Hayne E, 1994, Corporate Debt Value, Bond Covenants, and Optimal Capital Structure, *The Journal of Finance* 49, 1213–1252.

Leland, Hayne E., 1998, Agency costs, risk management, and capital structure, *Journal of Finance* 53, 1213–1243.

Lewis, Ryan, 2019, Same Firm , Different Betas, .

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *The Journal of Finance* 29, 449–470.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Ni, Sophie X., and Jun Pan, 2020, Trading Puts and CDS on Stocks with Short Sale Ban, *Workig Paper*.

Norden, Lars, and Martin Weber, 2009, The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis, *European Financial Management* 15, 529–562.

Sandulescu, Mirela, 2020, How Integrated Are Corporate Bond and Stock Markets?, .

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *The Journal of Finance* 52, 35–55.

Xu, Haohua, 2021, Are Option and CDS Markets Integrated?, .

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

Zviadadze, Irina, 2017, Term-Structure of Consumption Risk Premia in the Cross-Section of Currency Returns, *The Journal of Finance* 72, 1529–1566.

Figure 1: Credit spread term structures of Bear Stearns Cos Inc, Emulex Corp, and Sunoco Inc.

In this figure, we report the credit spread term structures of Bear Stearns Cos Inc (BSC), Emulex Corp (EMU), and Sunoco Inc (SUN) on 2008-04-04. Sources: Markit, authors' computation.

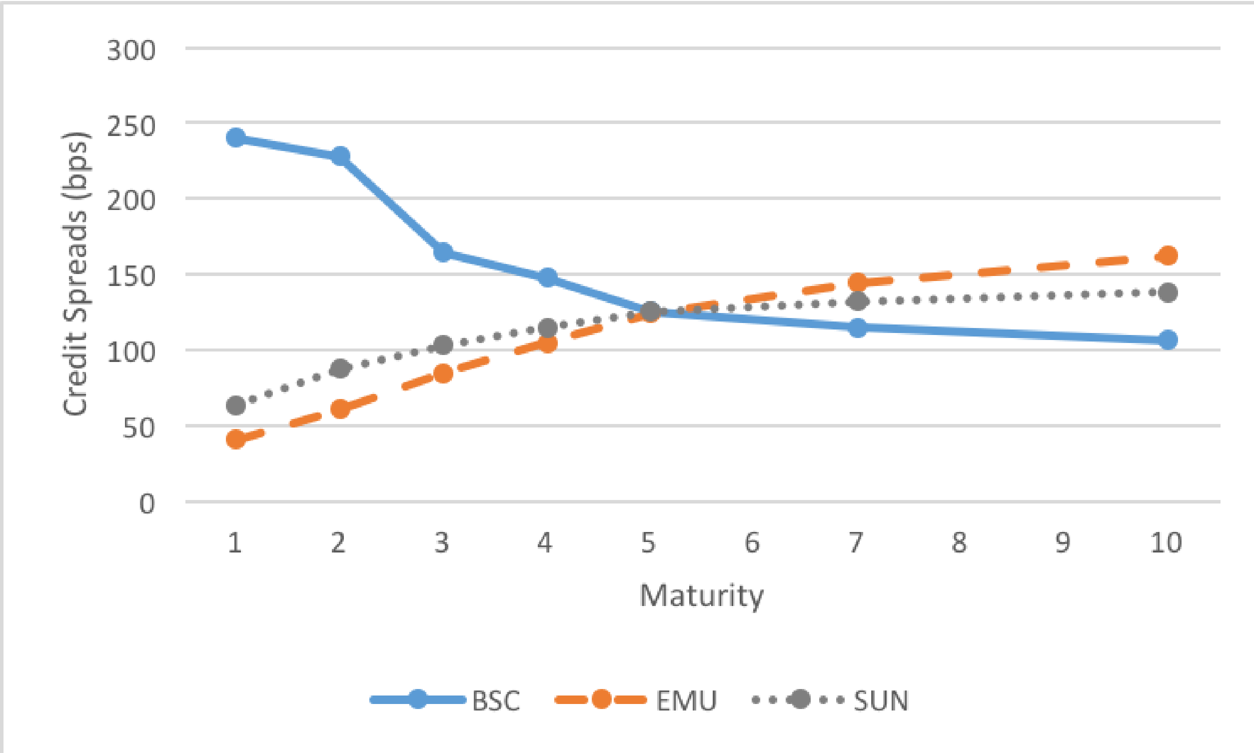


Figure 2: Returns on stock portfolios sorted by CDS spread level and CDS spread slope.

In this figure, we report the stock portfolio one month ahead returns sorted by the CDS spread level and slope. At each month, we first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, into five quintiles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. The data is at monthly frequency and the data period ranges from January 2002 until April 2018. Sources: Markit, CRSP, authors' computation.

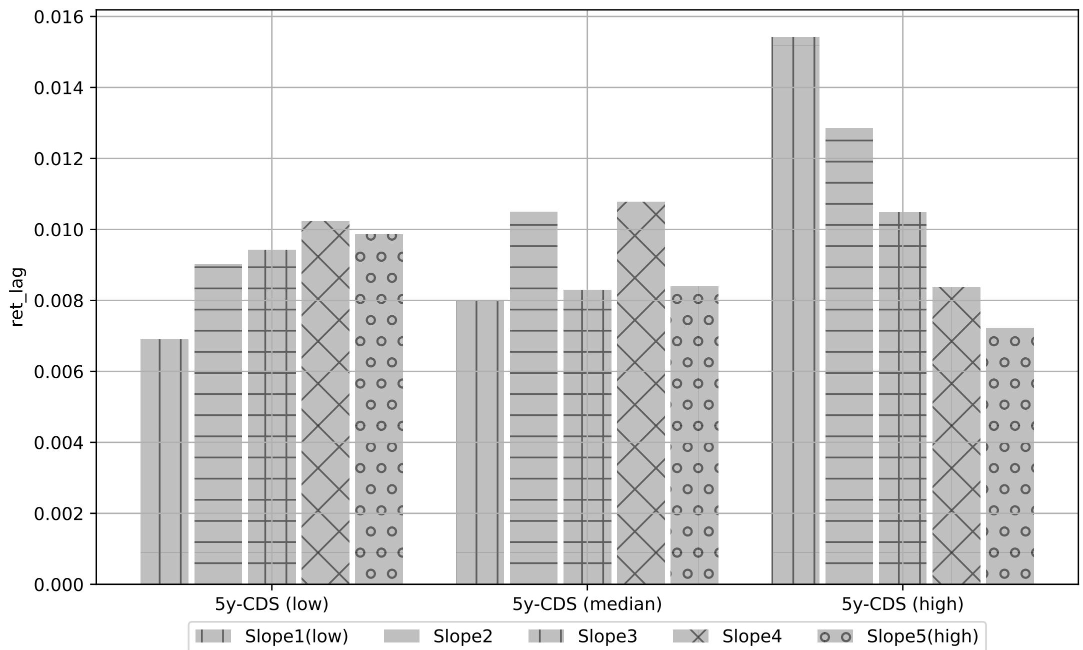
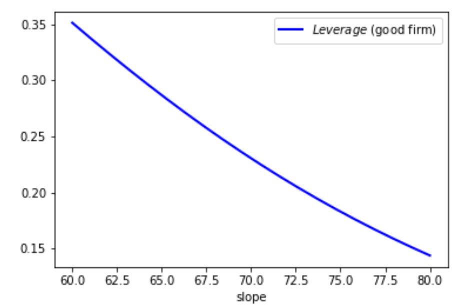


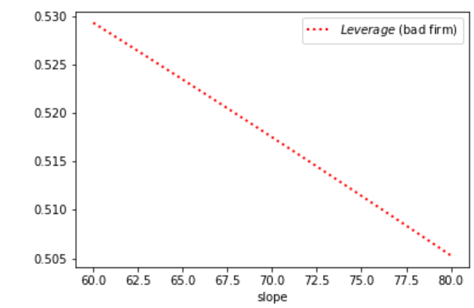
Figure 3: Comparative statics (Merton, 1974 model).

In this figure, we report the comparative statics for changes in the credit spread slope, defined as 10-year credit spread minus 1-year credit spread (measured in bps), under the Merton (1974) model. The first, second, and third row documents the evolution of leverage, asset volatility (σ), and equity risk premium (ERP), respectively. The first and second column describes the good and bad firm's quantities, respectively. We set the firm value to be 100, and interest rate to be 0.02, for both good and bad credit quality firms. We set the 5-year credit spread level to be 40 bps, sharpe ratio to be 0.2, loss given default to be 0.45 for good firms. We set the 5-year credit spread level to be 300 bps, sharpe ratio to be 0.08, loss given default to be 0.55 for bad firms. The credit spread slope ranges between 60 to 80 bps. To compute the equity risk premium, we set the maturity to be 1 year in the Merton model. The leverage is defined as the book value of debt divided by the sum of book value of debt and market value of the equity. Sources: Authors' computation.

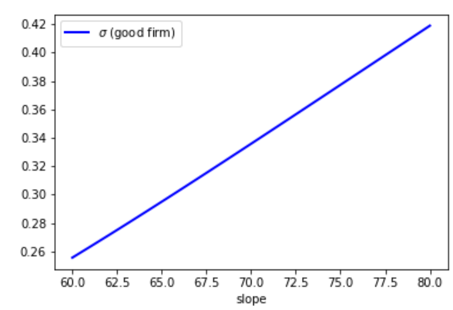
(A) Leverage



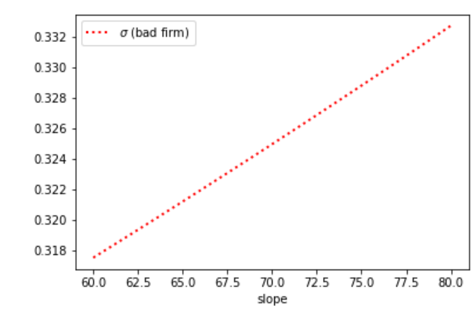
(B) Leverage



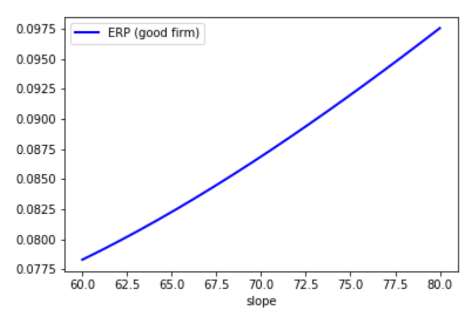
(C) Asset Volatility (σ)



(D) Asset Volatility (σ)



(E) ERP



(F) ERP

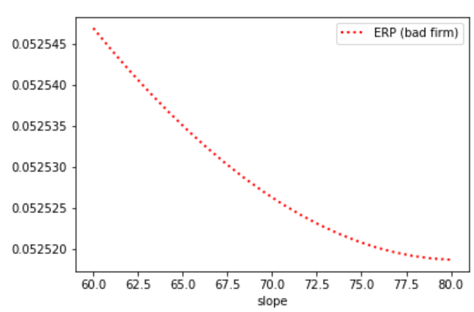
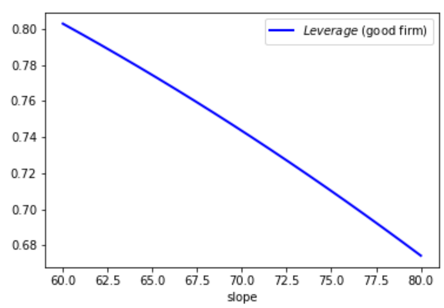


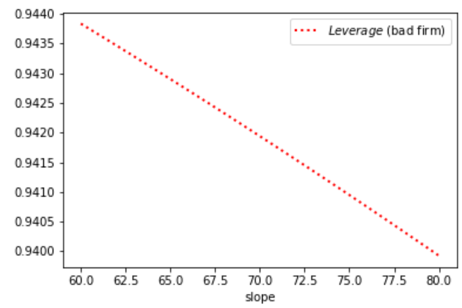
Figure 4: Comparative statics (Leland, 1994 model).

In this figure, we report the comparative statics for changes in the credit spread slope, defined as 10-year credit spread minus 1-year credit spread (measured in bps), under the Leland (1994) model. The first, second, and third row documents the evolution of leverage, asset volatility (σ), and equity risk premium (ERP), respectively. The first and second column describes the good and bad firm's quantities, respectively. We set the firm value to be 100, and interest rate to be 0.02, for both good and bad credit quality firms. We set the 5-year credit spread level to be 40 bps, sharpe ratio to be 0.2, loss given default to be 0.45 for good firms. We set the 5-year credit spread level to be 300 bps, sharpe ratio to be 0.08, loss given default to be 0.55 for bad firms. The credit spread slope ranges between 60 to 80 bps. The leverage is defined as the book value of debt divided by the sum of book value of debt and market value of the equity. Sources: Authors' computation.

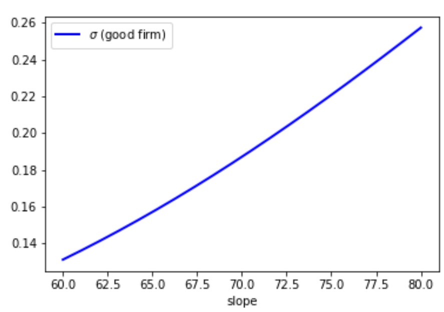
(A) Leverage



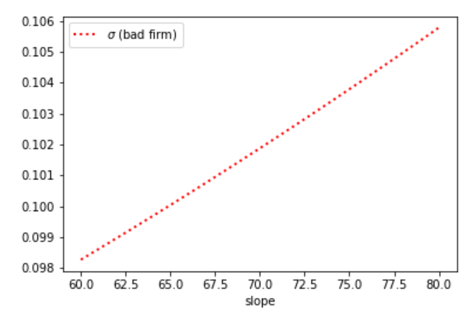
(B) Leverage



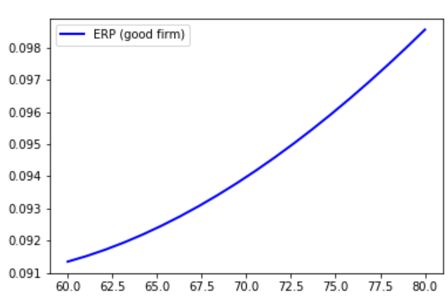
(C) Asset Volatility (σ)



(D) Asset Volatility (σ)



(E) ERP



(F) ERP

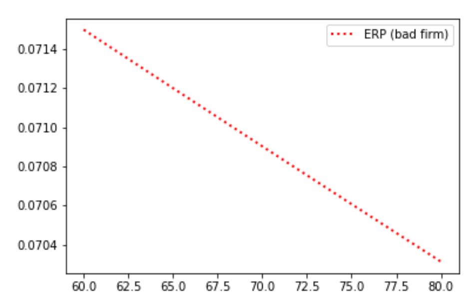


Figure 5: Returns on stock portfolios sorted by credit spread level and credit spread slope (Simulated data).

In this figure, we report the stock portfolio one month ahead returns sorted by the credit spread level and slope based on the Leland (1994) model simulated sample. At each month, we first sort the stocks based on the 5-year credit spread level into terciles. At each tercile, we then sort the stocks based on the credit spread slope, defined as 10-year credit spreads minus 1-year credit spreads, into five quintiles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. The data is at monthly frequency and the data period is 10 years. Sources: Authors' computation.

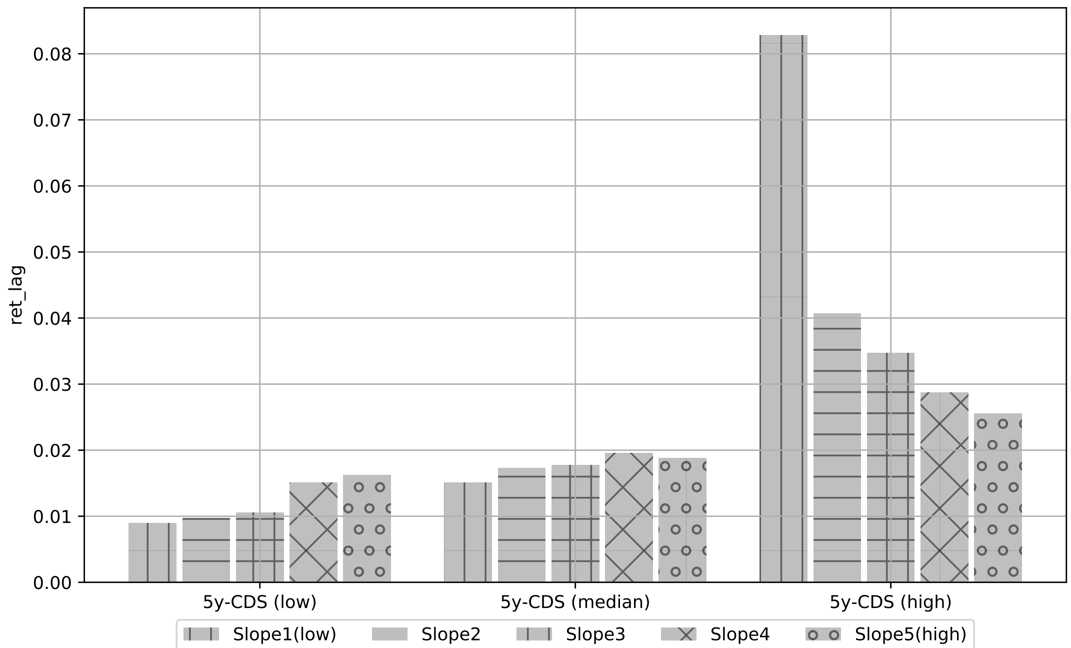


Table 1: Descriptive Statistics.

This table presents the cross-sectional descriptive statistics. We first compute the unconditional averages of the variables for each firm. We then generate the cross-sectional summary statistics of the CDS spreads, CDS spread slope, defined as 10-year CDS spreads minus 1-year CDS spreads, equity returns, leverage, equity volatility, log market capitalization (MC), measured in millions, book to market (BM), and rating. The data period ranges from January 2001 until March 2018. The data frequency is monthly. Sources: CRSP, Compustat, Markit, and authors' computations.

	obs.	#firms	mean	std	min	25%	50%	75%	max
1y-CDS	76517	759	0.021	0.124	0.001	0.003	0.006	0.015	3.308
5y-CDS	76517	759	0.025	0.062	0.002	0.006	0.012	0.027	1.471
10y-CDS	76517	759	0.027	0.048	0.002	0.008	0.015	0.030	1.044
Slope	76517	759	0.006	0.083	-2.264	0.004	0.007	0.013	0.085
Equity Return	76517	759	0.008	0.035	-0.452	0.005	0.010	0.016	0.202
Leverage	75975	752	0.352	0.217	0.001	0.185	0.302	0.487	0.972
Equity Volatility	76517	759	0.335	0.166	0.019	0.234	0.300	0.384	2.308
MktCap	76517	759	8.711	1.432	2.689	7.802	8.652	9.664	13.336
BM	72681	719	0.696	0.492	0.014	0.361	0.597	0.888	3.606
Rating	71479	737	4.203	1.061	1.000	3.490	4.000	5.000	7.077

Table 2: Returns on stock portfolios sorted by CDS spread level or slope.

In this table, we report the stock portfolio one month ahead returns sorted by the CDS spread level (panel A) or slope (panel B). We first sort the stocks into 10 deciles based on the CDS level, defined as 5-year CDS spreads, or slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Second, for each decile, we compute the equal weighted equity one month ahead return. Lastly, we compute the low - high long short portfolio return. The returns are in percentage terms. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, CRSP, author's computation.

Panel A: Sorted by CDS spread level											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	low - high
Average Return	0.67**	0.86***	0.95***	1.00***	1.04***	0.88**	0.88*	1.08*	1.10	0.90	−0.29
	t = 2.26	t = 2.83	t = 3.00	t = 2.85	t = 3.14	t = 2.18	t = 1.87	t = 1.94	t = 1.45	t = 1.12	t = −0.48
Panel B: Sorted by CDS spread slope											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	low - high
Average Return	1.42*	1.14**	1.03***	1.08***	0.85**	0.91**	0.87**	0.84**	0.94*	0.62	0.80*
	t = 1.76	t = 2.22	t = 2.69	t = 3.16	t = 2.45	t = 2.42	t = 2.02	t = 2.09	t = 1.73	t = 0.94	t = 1.75

Table 3: Predicting equity returns based on CDS spread levels and slopes.

In this table, I report the results of the following predictive panel regression:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta Var_{i,t} + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, Var_i denotes either the CDS spread level, defined as 5-year CDS spreads, or slope, defined as 10-year CDS spreads minus 1-year CDS spreads, α_i denotes the firm fixed effect, γ_t denotes the year-month (Columns (1) and (3)) or quarter (Columns (2) and (4)) fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, and stock daily return. When substituting the year-month fixed effect into quarter fixed effect, the regression is performed with additional macroeconomic controls. The macroeconomic control variables include CBOE VIX index, 10-year treasury yield, treasury yield slope, defined as 10-year yield minus 2-year yield, default spread, and TED spread. The data period ranges from January 2001 until March 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	(1) $R^{Eqty}_{i,t+1}$	(2) $R^{Eqty}_{i,t+1}$	(3) $R^{Eqty}_{i,t+1}$	(4) $R^{Eqty}_{i,t+1}$	(5)	(6)
5y-CDS	0.079	-0.073			0.182*	-0.038
	(1.048)	(-0.558)			(1.709)	(-0.270)
Slope			-0.329*	-0.453*	-0.432*	-0.448*
			(-1.775)	(-1.814)	(-1.911)	(-1.729)
Observations	72644	72622	72644	72622	72644	72622
R^2	0.263	0.136	0.264	0.137	0.264	0.137
Adjusted R^2	0.261	0.127	0.261	0.127	0.262	0.127
Firm FE		✓		✓		✓
Year-Month FE	✓		✓		✓	
Quarter FE		✓		✓		✓
Firm Control	✓	✓	✓	✓	✓	✓
Macro Control		✓		✓		✓

Table 4: Returns on stock portfolios sorted by CDS spread level and CDS spread slope.

In this table, we reports the stock portfolio one month ahead returns sorted by the CDS spread level and slope. At each month, we first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, into five quintiles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. Fourth, within each CDS tercile, we compute the low slope quintile minue high slope quintile portfolio return. Finally, we compute the time series averages of these portfolio returns. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, CRSP, author's computation.

	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.69**	0.90***	0.95***	1.03***	0.98***	−0.29**
	t = 2.58	t = 3.09	t = 3.23	t = 3.21	t = 3.00	t = −2.28
2	0.81**	1.02***	0.82**	1.08***	0.85**	−0.05
	t = 2.01	t = 2.85	t = 2.07	t = 2.73	t = 2.16	t = −0.25
3 (high CDS)	1.56*	1.28*	1.05*	0.85	0.71	0.84**
	t = 1.87	t = 1.85	t = 1.68	t = 1.35	t = 0.96	t = 1.98

Table 5: Predicting equity returns based on CDS slopes conditional on CDS spreads levels.

In this table, I report the results of the following predictive panel regression:

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + Y_{i,t}'\beta_Y + \epsilon_{i,t}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ in 3 different forms, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), $D_{highCDS,600bp}$ ($D_{lowCDS,30bp}$), and 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$) denotes the indicator variable which equals 1 if the firm's monthly CDS spreads are larger (smaller) than 600 (30) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, idiosyncratic risk, computed as the fraction of stock idiosyncratic volatility of the total stock volatility based on the Fama-French 3 factor model, stock daily return, and 5-year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	Full Sample					Ex. Crisis				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}
Slope	-0.473*	0.038	-0.443	-0.138	0.119	-0.485***	0.115	-0.445**	-0.181	-0.112
	(-1.720)	(0.116)	(-1.616)	(-0.756)	(0.569)	(-2.613)	(0.409)	(-2.421)	(-1.116)	(-0.601)
$D_{lowCDS,avg} \times Slope$	0.510**					0.600**				
	(2.025)					(2.280)				
$D_{highCDS,avg} \times Slope$		-0.510**					-0.600**			
		(-2.025)					(-2.281)			
$D_{lowCDS,50bp} \times Slope$			2.282**					2.683***		
			(2.098)					(2.786)		
$D_{highCDS,500bp} \times Slope$				-0.621*					-0.591***	
				(-1.898)					(-2.627)	
$CDS_{5y} \times Slope$					-9.033**					-5.802*
					(-2.536)					(-1.757)
Observations	72621	72621	72621	72621	72621	64058	64058	64058	64058	64058
R^2	0.282	0.282	0.282	0.282	0.282	0.244	0.244	0.244	0.244	0.244
Adjusted R^2	0.273	0.273	0.273	0.273	0.273	0.233	0.233	0.233	0.234	0.233
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 6: Double sort results based on different CDS slope definitions.

In this table, we reports the stock portfolio one month ahead returns sorted by the CDS spread level and slope. The CDS slope is defined as 10-year CDS spreads minus 2-year CDS spreads and 7-year CDS spreads minus 2-year CDS spreads. At each month, we first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope into five quintiles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. Fourth, within each CDS tercile, we compute the low slope quintile minue high slope quintile portfolio return. Finally, we compute the time series averages of these portfolio returns. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, CRSP, author's computation.

Panel A: $Slope = CDS_{10y} - CDS_{2y}$						
	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.66**	0.93***	0.99***	1.01***	0.96***	−0.30**
	t = 2.43	t = 3.27	t = 3.49	t = 3.05	t = 2.87	t = −2.12
2	0.87**	0.88**	0.94**	0.97**	0.93**	−0.06
	t = 2.05	t = 2.47	t = 2.38	t = 2.38	t = 2.43	t = −0.39
3 (high CDS)	1.63*	1.15	1.25*	0.88	0.54	1.08**
	t = 1.93	t = 1.60	t = 1.92	t = 1.40	t = 0.80	t = 2.32
Panel B: $Slope = CDS_{7y} - CDS_{2y}$						
	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.74***	0.87***	0.92***	1.00***	1.02***	−0.28**
	t = 2.68	t = 2.85	t = 3.04	t = 3.31	t = 3.03	t = −2.07
2	0.94**	0.80**	1.00**	0.93**	0.91**	0.03
	t = 2.56	t = 2.32	t = 2.50	t = 2.33	t = 2.19	t = 0.22
3 (high CDS)	1.51*	1.18*	1.09*	0.98	0.68	0.83*
	t = 1.74	t = 1.73	t = 1.86	t = 1.64	t = 0.86	t = 1.76

Table 7: Panel regression based on different CDS slope definitions.

In this table, We report the results of the following predictive panel regression based on different CDS slope definitions:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t Slope_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 2-year CDS spreads, or 7-year CDS spreads minus 2-year CDS spreads, and $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ in 3 different forms, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), $D_{highCDS,600bp}$ ($D_{lowCDS,30bp}$), and 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCDS,600bp}$ ($D_{lowCDS,30bp}$) denotes the indicator variable which equals 1 if the firm's monthly CDS spreads are larger (smaller) than 600 (30) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	(1) R^{Eqty}_{t+1}	(2) R^{Eqty}_{t+1}	(3) R^{Eqty}_{t+1}	(4) R^{Eqty}_{t+1}	(5) R^{Eqty}_{t+1}	(1) R^{Eqty}_{t+1}	(2) R^{Eqty}_{t+1}	(3) R^{Eqty}_{t+1}	(4) R^{Eqty}_{t+1}	(5) R^{Eqty}_{t+1}
Panel A: $Slope = CDS_{10y} - CDS_{2y}$						**Panel B:** $Slope = CDS_{7y} - CDS_{2y}$				
Slope	-0.564*	0.013	-0.529*	-0.152	0.339	-0.677*	-0.126	-0.643*	-0.345	0.040
	(-1.849)	(0.037)	(-1.745)	(-0.770)	(1.436)	(-1.826)	(-0.293)	(-1.733)	(-1.378)	(0.151)
$D_{lowCDS,avg} \times Slope$	0.577**					0.551*				
	(2.008)					(1.680)				
$D_{highCDS,avg} \times Slope$		-0.577**					-0.551*			
		(-2.008)					(-1.680)			
$D_{lowCDS,30bp} \times Slope$			2.474**					3.150*		
			(2.166)					(1.908)		
$D_{highCDS,600bp} \times Slope$				-0.798*					-0.652	
				(-1.933)					(-1.649)	
$CDS_{5y} \times Slope$					-13.724***					-11.176**
					(-2.929)					(-2.520)
Observations	72622	72622	72622	72622	72622	72622	72622	72622	72622	72622
R^2	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282
Adjusted R^2	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 8: Double sort results controlled for informed trading proxies. In this table, we report the stock portfolio one month ahead returns sorted by the CDS spread level and slope, after removing firms that are less transparent. The CDS slope is defined as 10-year CDS spreads minus 1-year CDS spreads. We first remove firms with average transparency proxy ranked among the top quarter. The transparency proxy includes CDS depth, idiosyncratic risk, institutional ownership, analyst coverage, and firm size. At each month, we first sort the stocks based on the 5-year CDS spread level into quartiles. At each quartile, we then sort the stocks based on the CDS slope into five tercile. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. Fourth, within each CDS quartile, we compute the low slope tercile minue high slope tercile portfolio return. Finally, we compute the time series averages of these portfolio returns. The returns are in percentage terms. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, CRSP, author's computation.

Panel A: CDS Depth

	1 (low slope)	2	3 (high slope)	low - high
low CDS	0.74***	0.94***	0.98***	−0.24**
	t = 2.63	t = 3.32	t = 3.24	t = −1.98
high CDS	1.58**	0.99	0.60	0.99**
	t = 1.98	t = 1.39	t = 0.85	t = 2.17

Panel B: Idiosyncratic Risk

	1 (low slope)	2	3 (high slope)	low - high
low CDS	0.67**	0.95***	1.04***	−0.37***
	t = 2.29	t = 3.06	t = 3.37	t = −3.02
high CDS	1.65**	1.24*	0.84	0.81*
	t = 2.12	t = 1.72	t = 1.12	t = 1.77

Panel C: Institutional Ownership

	1 (low slope)	2	3 (high slope)	low - high
low CDS	0.83***	1.02***	0.97***	−0.14
	t = 2.78	t = 3.42	t = 2.91	t = −1.01
high CDS	1.61*	1.09	0.74	0.87*
	t = 1.89	t = 1.51	t = 1.03	t = 1.96

Panel D: Analyst Coverage

	1 (low slope)	2	3 (high slope)	low - high
low CDS	0.74**	0.89***	1.06***	−0.32***
	t = 2.59	t = 2.96	t = 3.56	t = −2.62
high CDS	1.58**	1.19*	0.51	1.07**
	t = 2.04	t = 1.80	t = 0.72	t = 2.29

Panel E: Size

	1 (low slope)	2	3 (high slope)	low - high
low CDS	0.73***	0.89***	0.94***	−0.21*
	t = 2.65	t = 3.00	t = 3.35	t = −1.81
high CDS	1.47**	1.14**	0.79	0.68*
	t = 2.12	t = 2.05	t = 1.32	t = 1.68

Table 9: Predicting equity returns based on CDS slopes conditional on levels of CDS spreads controlled for informed trading.

In this table, I report the results of the following predictive panel regression:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + \beta_{informed} Informed_t Slope_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ captures the CDS slope predictive effect conditional on the CDS spread level, and $Informed_t Slope_t$ captures the predictive effect of the slope conditional on the firm's transparency level. We specify $Level_t$ in 3 different forms, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), $D_{highCDS,600bp}$ ($D_{lowCDS,30bp}$), and 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$) denotes the indicator variable which equals 1 if the firm's monthly CDS spreads are larger (smaller) than 600 (30) bps and 0 otherwise. $Informed_t$ denotes the firm's transparency proxies, such as the firm's CDS depth, idiosyncratic risk ($Idiosyn$), institutional ownership (IO), analyst coverage ($\#Analyst$), and market capitalization ($MktCap$). β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	(1) R^{Eqty}_{t+1}	(2) R^{Eqty}_{t+1}	(3) R^{Eqty}_{t+1}	(4) R^{Eqty}_{t+1}	(5) R^{Eqty}_{t+1}	(6) R^{Eqty}_{t+1}	(7) R^{Eqty}_{t+1}	(8) R^{Eqty}_{t+1}	(9) R^{Eqty}_{t+1}	(10) R^{Eqty}_{t+1}	(11) R^{Eqty}_{t+1}	(12) R^{Eqty}_{t+1}	(13) R^{Eqty}_{t+1}	(14) R^{Eqty}_{t+1}	(15) R^{Eqty}_{t+1}
Slope	-0.712**	-0.661*	-1.075**	-0.422	-1.394	-0.355	-0.298	-0.766*	-0.037	-1.105	0.077	0.110	-0.364	0.467*	-0.339
	(-2.145)	(-1.914)	(-2.340)	(-1.168)	(-1.296)	(-1.364)	(-1.222)	(-1.937)	(-0.137)	(-1.033)	(0.304)	(0.513)	(-1.002)	(1.765)	(-0.282)
$D_{lowCDS} \times Slope$	0.357**	0.363**	0.309**	0.385**	0.289**										
	(2.289)	(2.352)	(2.075)	(2.449)	(2.162)										
$D_{highCDS} \times Slope$						-0.357**	-0.363**	-0.309**	-0.385**	-0.289**					
						(-2.289)	(-2.352)	(-2.075)	(-2.449)	(-2.162)					
$CDS_{5y} \times Slope$											-8.940**	-9.094**	-7.909**	-9.948***	-8.015**
											(-2.461)	(-2.527)	(-2.247)	(-2.724)	(-2.199)
$Depth \times Slope$	0.010					0.010					0.006				
	(0.327)					(0.327)					(0.178)				
$Idiosyn \times Slope$		0.023					0.023					0.028			
		(0.330)					(0.330)					(0.401)			
$IO \times Slope$			0.615*					0.615*					0.558*		
			(1.808)					(1.808)					(1.693)		
$\#Analyst \times Slope$				-0.022*					-0.022*					-0.026**	
				(-1.880)					(-1.880)					(-2.230)	
$MktCap \times Slope$					0.102					0.102					0.051
					(0.911)					(0.911)					(0.421)
Observations	72621	72622	72616	72299	72622	72621	72622	72616	72299	72622	72621	72622	72616	72299	72622
R^2	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.283	0.282
Adjusted R^2	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 10: Predicting equity returns based on CDS slopes conditional on CDS spreads levels (control for industry effect).

In this table, I report the results of the following predictive panel regression:

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \delta_{ind} + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + Y_{i,t}' \beta_Y + \epsilon_{i,t}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ in 3 different forms, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), $D_{highCDS,600bp}$ ($D_{lowCDS,30bp}$), and 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$) denotes the indicator variable which equals 1 if the firm's monthly CDS spreads are larger (smaller) than 600 (30) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, δ_{ind} denotes the industry fixed effect, where the industry definitions are based on Fama-French definition, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	Full Sample					Ex. Crisis				
	(1) R_{t+1}^{Eqty}	(2) R_{t+1}^{Eqty}	(3) R_{t+1}^{Eqty}	(4) R_{t+1}^{Eqty}	(5) R_{t+1}^{Eqty}	(6) R_{t+1}^{Eqty}	(7) R_{t+1}^{Eqty}	(8) R_{t+1}^{Eqty}	(9) R_{t+1}^{Eqty}	(10) R_{t+1}^{Eqty}
Slope	-0.462*	0.018	-0.433	-0.135	0.111	-0.471**	0.097	-0.432**	-0.172	-0.115
	(-1.666)	(0.054)	(-1.570)	(-0.729)	(0.529)	(-2.593)	(0.339)	(-2.401)	(-1.060)	(-0.612)
$D_{lowCDS,avg} \times Slope$	0.480*					0.568**				
	(1.888)					(2.139)				
$D_{highCDS,avg} \times Slope$		-0.480*					-0.568**			
		(-1.888)					(-2.139)			
$D_{lowCDS,30bp} \times Slope$			2.159**					2.542***		
			(2.060)					(2.757)		
$D_{highCDS,600bp} \times Slope$				-0.607*					-0.578**	
				(-1.853)					(-2.581)	
$CDS_{5y} \times Slope$					-8.758**					-5.516*
					(-2.484)					(-1.695)
Observations	72533	72533	72533	72533	72533	63970	63970	63970	63970	63970
R^2	0.282	0.282	0.282	0.283	0.283	0.245	0.245	0.245	0.245	0.245
Adjusted R^2	0.273	0.273	0.273	0.273	0.273	0.234	0.234	0.234	0.234	0.234
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 11: Returns on stock portfolios sorted by bond yield level and bond yield slope. In this table, we reports the stock portfolio one month ahead returns sorted by the bond yield level and slope. The yield level is defined as the median term yield, which is the average bond yield with maturity between 4-9 years. The slope is defined as the long term yield minus the short term yield, where the short term yield is the average bond yield with maturity smaller than 4 years and the long term yield is the average bond yield with maturity greater than 9 years. At each month, we first sort the stocks based on the median bond yield level into terciles. At each tercile, we then sort the stocks based on the bond yield slope into three terciles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. Fourth, within each level tercile, we compute the low slope tercile minue high slope tercile portfolio return. Finally, we compute the time series averages of these portfolio returns. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: TRACE, CRSP, WRDS, author's computation.

	1 (low slope)	2	3 (high slope)	low - high
1 (low yield)	0.44	0.64	0.99***	−0.55*
	t = 1.10	t = 1.32	t = 2.96	t = −1.75
2	1.12**	1.20**	1.01**	0.11
	t = 2.04	t = 2.03	t = 2.47	t = 0.29
3 (high yield)	1.38*	0.56	0.08	1.30**
	t = 1.80	t = 0.68	t = 0.11	t = 2.34

Table 12: Predicting equity returns using bond yield slopes conditional on levels of bond yields.

In this table, I report the results of the following predictive panel regression:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the bond yield slope, defined as long term bond yields minus short term bond yields, $Level_t \times Slope_t$ capture the slope predictive effect conditional on the bond yield level. The yield level is defined as the median term yield, which is the average bond yield with maturity between 4-9 years. The short term yield is the average bond yield with maturity smaller than 4 years and the long term yield is the average bond yield with maturity greater than 9 years. We specify $Level_t$ in 3 different forms, $D_{highyield,avg}$ ($D_{lowyield,avg}$), $D_{highyield,750bp}$ ($D_{lowyield,250bp}$) and median term yields, where $D_{highyield,avg}$ ($D_{lowyield,avg}$) denotes the indicator variable which equals 1 if the firm's average median term yield level belonging to the top (bottom) half and 0 otherwise, and $D_{highyield,750bp}$ ($D_{lowyield,250bp}$) denotes the indicator variable which equals 1 if the firm's monthly median term yields are larger (smaller) than 750 (250) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the yield slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, idiosyncratic risk, computed as the fraction of stock idiosyncratic volatility of the total stock volatility based on the Fama-French 3 factor model, stock daily return, and median term bond yields. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	Full Sample					Ex. Crisis				
	(1) R^{Eqty}_{t+1}	(2) R^{Eqty}_{t+1}	(3) R^{Eqty}_{t+1}	(4) R^{Eqty}_{t+1}	(5) R^{Eqty}_{t+1}	(6) R^{Eqty}_{t+1}	(7) R^{Eqty}_{t+1}	(8) R^{Eqty}_{t+1}	(9) R^{Eqty}_{t+1}	(10) R^{Eqty}_{t+1}
Slope	-0.244	0.141	-0.173	0.066	0.635**	-0.505***	-0.080	-0.442***	0.061	1.014**
	(-1.576)	(0.657)	(-1.051)	(0.384)	(2.560)	(-3.100)	(-0.365)	(-2.749)	(0.297)	(2.322)
$D_{lowyield,avg} \times Slope$	0.471**					0.451**				
	(2.283)					(2.101)				
$D_{highyield,avg} \times Slope$		-0.514*					-0.636*			
		(-1.873)					(-1.721)			
$D_{lowyield,50bp} \times Slope$			0.611					0.847**		
			(1.585)					(2.122)		
$D_{highyield,500bp} \times Slope$				-0.270					-0.883**	
				(-0.936)					(-2.080)	
$yield_{median} \times Slope$					-7.418***					-15.329***
					(-3.381)					(-2.854)
Observations	6348	6348	6348	6348	6348	5805	5805	5805	5805	5805
R^2	0.323	0.323	0.322	0.326	0.325	0.286	0.287	0.286	0.290	0.295
Adjusted R^2	0.287	0.287	0.286	0.290	0.289	0.247	0.248	0.247	0.252	0.257
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 13: Model parameters.

In this table, I report the parameters for the comparative statics and simulation exercise. Sources: authors' computation.

Parameters	High Credit Quality Firms	Low Credit Quality Firms	Sources
Target credit spread (5y)	40 bps	300 bps	Authors' computation
Sharpe ratio SR	0.2	0.08	Chen, Collin-Dufresne, and Goldstein (2009) and authors' computation
Loss given default L	0.45	0.55	Elton, Gruber, Agrawal, and Mann (2001) and Huang and Huang (2012)
Tax rate (τ)	0.15	0.15	Du, Elkamhi, and Ericsson (2019)
Bankruptcy cost (α)	0.15	0.15	Du, Elkamhi, and Ericsson (2019)
Firm value V	100	100	
Risk free rate r	0.02	0.02	

Table 14: Returns on stock portfolios sorted by credit spread level and credit spread slope (Simulated data).

In this table, we reports the stock portfolio one month ahead returns sorted by the credit spread level and slope based on the Leland (1994) model simulated sample. At each month, we first sort the stocks based on the 5-year credit spread level into terciles. At each tercile, we then sort the stocks based on the credit spread slope, defined as 10-year credit spreads minus 1-year credit spreads, into five quintiles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. Fourth, within each level tercile, we compute the low slope quintile minue high slope quintile portfolio return. Finally, we compute the time series averages of these portfolio returns. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period 10 years. Sources: Author's computation.

	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.89***	0.97***	1.06**	1.51***	1.62***	−0.73***
	t = 2.98	t = 3.09	t = 2.60	t = 3.54	t = 3.83	t = −3.12
2	1.51***	1.73***	1.77***	1.96***	1.88***	−0.38
	t = 3.05	t = 3.45	t = 3.16	t = 3.29	t = 3.13	t = −1.25
3 (high CDS)	8.28***	4.07***	3.47***	2.87***	2.55***	5.73***
	t = 7.85	t = 4.16	t = 3.93	t = 3.43	t = 3.24	t = 9.79

Table 15: Predicting equity returns based on credit spread slopes conditional on credit spreads levels (Simulated data).

In this table, I report the results of the following predictive panel regression based on the Leland (1994) model simulated sample:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the credit slope, defined as 10-year credit spreads (CS) minus 1-year credit spreads, $Level_t \times Slope_t$ capture the credit slope predictive effect conditional on the credit spread level. We specify $Level_t$ in 3 different forms, $D_{highCS,avg}$ ($D_{lowCS,avg}$), $D_{highCS,400bp}$ ($D_{lowCS,150bp}$), and 5y-credit spreads, where $D_{highCS,avg}$ ($D_{lowCS,avg}$) denotes the indicator variable which equals 1 if the firm's average credit spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCS,400bp}$ ($D_{lowCS,150bp}$) denotes the indicator variable which equals 1 if the firm's monthly credit spreads are larger (smaller) than 400 (150) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the credit spread slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, and 5-year credit spreads. The data period is 10 years. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Author's computation.

	(1)	(2)	(3)	(4)	(5)
	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}
Slope	-0.325***	-0.093	-0.404***	1.000**	0.842***
	(-5.528)	(-1.099)	(-6.200)	(2.161)	(2.831)
$D_{lowCS,avg} \times Slope$	1.639***				
	(3.262)				
$D_{highCS,avg} \times Slope$		-0.318***			
		(-4.027)			
$D_{lowCS,150bp} \times Slope$			1.458***		
			(3.390)		
$D_{highCS,400bp} \times Slope$				-1.408***	
				(-2.917)	
$CS_{5y} \times Slope$					-12.670***
					(-3.927)
Observations	105798	105798	105798	105798	105798
R^2	0.136	0.136	0.136	0.136	0.136
Adjusted R^2	0.126	0.126	0.126	0.126	0.126
Firm FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓

A Studies on credit market and its relation with equity market

Table A1: Literature on the relation between credit and equity markets

	Type		Focus		Economic mechanism		
[60]Study	[60]Empirics	[60]Theory	[60]Level	[60]Term Structure	[60]Informed Trading	[60]Market Imperfection	[60]Frictionless
Acharya and Johnson (2007)	✓		✓		✓		
Hilscher, Pollet, and Wilson (2015)	✓		✓		✓	✓	
Ni and Pan (2020)	✓		✓			✓	
Lee, Naranjo, and Velioglu (2018)	✓		✓		✓		
Norden and Weber (2009)	✓		✓				
Han, Subrahmanyam, and Zhou (2017)	✓			✓	✓		
The present study	✓	✓		✓			✓

Notes. This table summarizes the main studies on the relation between equity and credit markets. We describe the type of study (empirical or theoretical), the focus of the paper (credit spread level or term structure), and the main economic mechanism proposed by each study.

B Corporate bond data summary

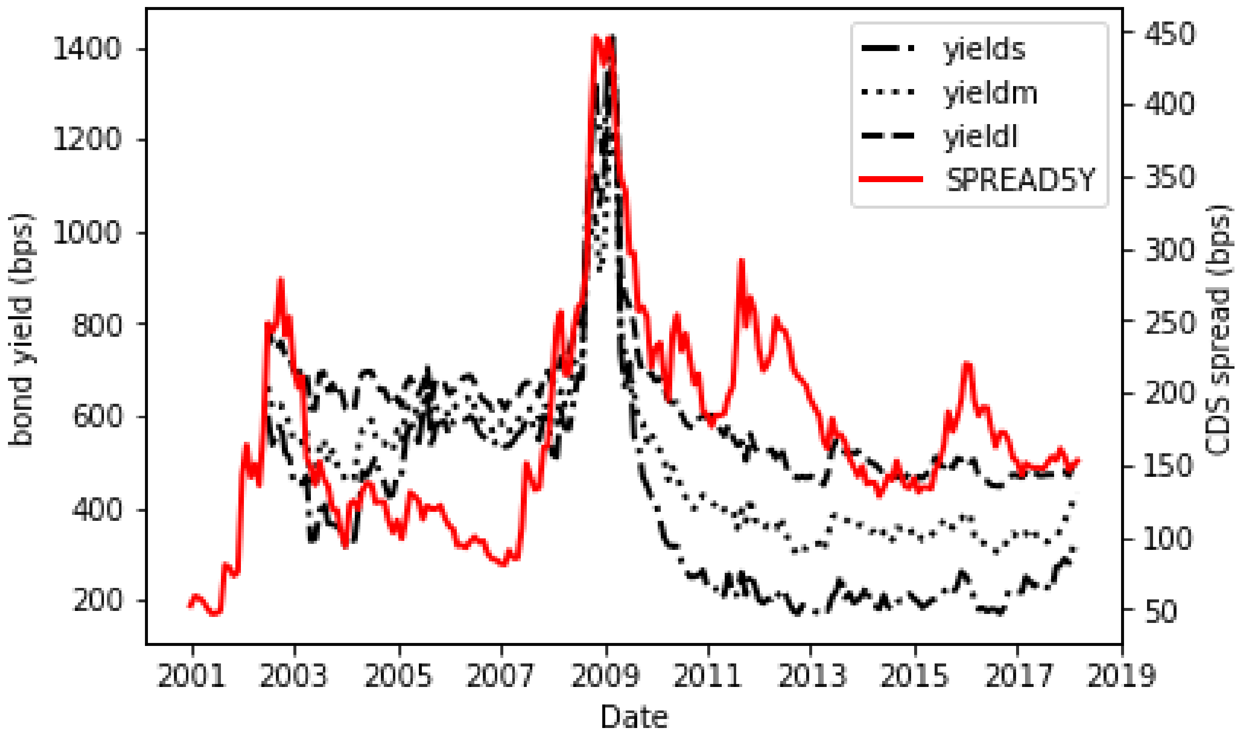
Table A2: Corporate Bond Descriptive Statistics.

This table presents the cross-sectional descriptive statistics of corporate bond data. We first compute the unconditional averages of the variables for each firm. We then generate the cross-sectional summary statistics of the long, median, and short term bond yield, bond yield slope, defined as long term yields minus short term yields, equity returns, leverage, equity volatility, log market capitalization (MC), measured in millions, book to market (BM), and rating. We compute the short term yield as the average bond yield with maturity smaller than 4 years, median term yield as the average bond yield with maturity greater than 4 years but smaller than 9 years, and the long term yield as the average bond yield with maturity greater than 9 years. The data period ranges from January 2001 until March 2018. The data frequency is monthly. Sources: CRSP, Compustat, TRACE, and authors' computations.

	obs.	#firms	mean	std	min	25%	50%	75%	max
$Yield_s$	6520	130	0.044	0.037	0.007	0.028	0.035	0.046	0.318
$Yield_m$	6520	130	0.052	0.027	0.010	0.039	0.046	0.055	0.253
$Yield_l$	6520	130	0.064	0.024	0.021	0.052	0.059	0.068	0.222
Slope	6520	130	0.020	0.016	-0.096	0.018	0.023	0.027	0.057
Equity Return	6520	130	0.008	0.032	-0.125	-0.002	0.009	0.016	0.126
Leverage	6506	129	0.412	0.241	0.034	0.209	0.365	0.552	0.952
Equity Volatility	6520	130	0.314	0.159	0.120	0.214	0.279	0.356	1.107
MktCap	6520	130	9.724	1.345	6.526	8.882	9.728	10.623	12.589
BM	6357	128	0.769	0.630	0.015	0.430	0.663	0.926	4.039
Rating	6310	129	3.583	1.052	1.000	3.000	3.250	4.000	6.013

Figure A1: Aggregate CDS Spreads and bond yields time series plot.

In this figure, I report the monthly time series of aggregate 5-year CDS spreads (red solid line, in bps), and the bond yields (black line, in bps), with short, median, and long term maturity. We compute the short term yield as the average bond yield with maturity smaller than 4 years, median term yield as the average bond yield with maturity greater than 4 years but smaller than 9 years, and the long term yield as the average bond yield with maturity greater than 9 years. The aggregate time series is computed as cross sectional averages of the CDS spread and the bond yields. The data period ranges from January 2001 until March 2018. Sources: Markit, TRACE, authors' computation.



C Proof of Theorem 1

Proof. The following equation solves a firm's asset volatility and default boundary given credit spread level and slope:

$$\begin{aligned}
&\frac{1}{T_2}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right)-\left(r-\frac{1}{2}\sigma^2\right)T_2}{\sigma\sqrt{T_2}}\right)-\frac{1}{T_1}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right)-\left(r-\frac{1}{2}\sigma^2\right)T_1}{\sigma\sqrt{T_1}}\right)-slope=0\\
&\frac{1}{T}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right)-\left(r-\frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}\right)-level=0.
\end{aligned}\tag{1}$$

In the following proof, we compute the partial derivatives of default boundary V_B and asset volatility σ with respect to the credit spread slope to rationalize our empirical results.

Suppose x is the solution to a system of non-linear equations $D(x,\theta)=0$, where θ is the parameter vector of the equations, according to Implicit Function Theorem:

$$\frac{\partial x(\theta)}{\partial\theta_i}=-\left[\frac{\partial D_i(x(\theta),\theta)}{\partial x_j}\right]^{-1}\left[\frac{\partial D(x(\theta),\theta)}{\partial\theta_i}\right].\tag{2}$$

In this exercise, we solve for V_B and σ from Equation (1). Hence,

$$\begin{aligned}
D(x,\theta)&=\begin{bmatrix}\frac{1}{T_2}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right)-\left(r-\frac{1}{2}\sigma^2\right)T_2}{\sigma\sqrt{T_2}}\right)-\frac{1}{T_1}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right)-\left(r-\frac{1}{2}\sigma^2\right)T_1}{\sigma\sqrt{T_1}}\right)-slope\\ \frac{1}{T}N\left(\frac{\log\left(\frac{V_B}{V(t)}\right)-\left(r-\frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}\right)-level\end{bmatrix}\\
x&=\begin{bmatrix}V_B\\ \sigma\end{bmatrix}\\
\theta&=\begin{bmatrix}slope, level\end{bmatrix}.
\end{aligned}\tag{3}$$

The Jacobian matrix of $D(x,\theta)$ can be written as

$$\begin{aligned}
&\left[\frac{\partial D_i(x(\theta),\theta)}{\partial x_j}\right]\\
&=\begin{pmatrix}
\frac{1}{T_2}\phi\left(-d_2(T_2)\right)\frac{1}{\sigma\sqrt{T_2}}\frac{1}{V_B}-\frac{1}{T_1}\phi\left(-d_2(T_1)\right)\frac{1}{\sigma\sqrt{T_1}}\frac{1}{V_B} & \frac{1}{T_2}\phi\left(-d_2(T_2)\right)\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T_2}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T_2}}{2}+\frac{r\sqrt{T_2}}{\sigma^2}\right)\\
 & -\frac{1}{T_1}\phi\left(-d_2(T_1)\right)\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T_1}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T_1}}{2}+\frac{r\sqrt{T_1}}{\sigma^2}\right)\\
\frac{1}{T}\phi\left(-d_2(T)\right)\frac{1}{\sigma\sqrt{T}}\frac{1}{V_B} & \frac{1}{T}\phi\left(-d_2(T)\right)\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T}}{2}+\frac{r\sqrt{T}}{\sigma^2}\right)
\end{pmatrix}
\end{aligned}\tag{4}$$

Therefore,

$$\begin{aligned}
det\left[\frac{\partial D_i(x(\theta),\theta)}{\partial x_j}\right] &= \frac{1}{TT_2}\phi\left(-d_2(T)\right)\phi\left(-d_2(T_2)\right)\frac{1}{\sigma\sqrt{T_2}}\frac{1}{V_B}\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T}}{2}+\frac{r\sqrt{T}}{\sigma^2}\right) \\
&- \frac{1}{TT_1}\phi\left(-d_2(T)\right)\phi\left(-d_2(T_1)\right)\frac{1}{\sigma\sqrt{T_1}}\frac{1}{V_B}\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T}}{2}+\frac{r\sqrt{T}}{\sigma^2}\right) \\
&- \frac{1}{TT_2}\phi\left(-d_2(T)\right)\phi\left(-d_2(T_2)\right)\frac{1}{\sigma\sqrt{T}}\frac{1}{V_B}\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T_2}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T_2}}{2}+\frac{r\sqrt{T_2}}{\sigma^2}\right) \\
&+ \frac{1}{TT_1}\phi\left(-d_2(T)\right)\phi\left(-d_2(T_1)\right)\frac{1}{\sigma\sqrt{T}}\frac{1}{V_B}\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T_1}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T_1}}{2}+\frac{r\sqrt{T_1}}{\sigma^2}\right), \\
&= \frac{1}{TT_1}\phi\left(-d_2(T)\right)\phi\left(-d_2(T_1)\right)\frac{1}{\sigma V_B}\left(\frac{1}{2}+\frac{r}{\sigma^2}\right)\left(\frac{\sqrt{T_1}}{\sqrt{T}}-\frac{\sqrt{T}}{\sqrt{T_1}}\right) \\
&+ \frac{1}{TT_2}\phi\left(-d_2(T)\right)\phi\left(-d_2(T_2)\right)\frac{1}{\sigma V_B}\left(\frac{1}{2}+\frac{r}{\sigma^2}\right)\left(\frac{\sqrt{T}}{\sqrt{T_2}}-\frac{\sqrt{T_2}}{\sqrt{T}}\right) \\
&< 0
\end{aligned} \tag{5}$$

where $-d_2(T) = \frac{\log\left(\frac{V_B}{V(t)}\right)-\left(r-\frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}$, and the last inequality is valid when $T_1 \leqslant T \leqslant T_2$.

Based on these quantities,

$$\left[\frac{\partial D_i(x(\theta),\theta)}{\partial x_j}\right]^{-1} = \frac{1}{det\left[\frac{\partial D_i(x(\theta),\theta)}{\partial x_j}\right]}\begin{bmatrix} \frac{1}{T}\phi\left(-d_2(T)\right)\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T}}{2}+\frac{r\sqrt{T}}{\sigma^2}\right) & -\frac{1}{T_2}\phi\left(-d_2(T_2)\right)\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T_2}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T_2}}{2}+\frac{r\sqrt{T_2}}{\sigma^2}\right) \\ & +\frac{1}{T_1}\phi\left(-d_2(T_1)\right)\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T_1}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T_1}}{2}+\frac{r\sqrt{T_1}}{\sigma^2}\right) \\ -\frac{1}{T}\phi\left(-d_2(T)\right)\frac{1}{\sigma\sqrt{T}}\frac{1}{V_B} & \frac{1}{T_2}\phi\left(-d_2(T_2)\right)\frac{1}{\sigma\sqrt{T_2}}\frac{1}{V_B}-\frac{1}{T_1}\phi\left(-d_2(T_1)\right)\frac{1}{\sigma\sqrt{T_1}}\frac{1}{V_B} \end{bmatrix} \tag{6}$$

Furthermore, since $\left[\frac{\partial D(x(\theta),\theta)}{\partial slope}\right] = \begin{bmatrix} -1 \\ 0 \end{bmatrix}$, based on Equation (2), $\frac{\partial V_B}{\partial slope}$ and $\frac{\partial \sigma}{\partial slope}$ can be expressed as:

$$\begin{bmatrix} \frac{\partial V_B}{\partial slope} \\ \frac{\partial \sigma}{\partial slope} \end{bmatrix} = -\frac{1}{det\left[\frac{\partial D_i(x(\theta),\theta)}{\partial x_j}\right]}\begin{bmatrix} -\frac{1}{T}\phi\left(-d_2(T)\right)\left(\frac{\log\left(\frac{V_B}{V(t)}\right)}{\sqrt{T}}\left(-\frac{1}{\sigma^2}\right)+\frac{\sqrt{T}}{2}+\frac{r\sqrt{T}}{\sigma^2}\right) \\ \frac{1}{T}\phi\left(-d_2(T)\right)\frac{1}{\sigma\sqrt{T}}\frac{1}{V_B} \end{bmatrix}. \tag{7}$$

As a result,

$$\begin{aligned} &\frac{\partial V_B}{\partial slope} < 0 \\ &\frac{\partial \sigma}{\partial slope} > 0 \end{aligned} \tag{8}$$

□

D Leland (1994) model

In this section, we apply the Leland (1994) framework to understand 1) the predictive power of the credit spread slope on equity returns, conditional on the credit spread level; 2) the different signs of the predictability conditional on high and low credit spread level.

Following Leland (1994), we assume that the firm value is assumed to follow the following Geometric Brownian Motion:

$$\begin{aligned}\frac{dV_t}{V_t} &= \mu^P dt + \sigma dW_t^P \\ &= r dt + \sigma dW_t^Q,\end{aligned} \tag{9}$$

under the physical and risk neutral measure, respectively. $\mu^P = r + \lambda\sigma$, where λ is the market price of risk. Suppose that the firm issues a perpetual debt that pays a coupon C per instant of time if the firm is solvent. The firm defaults when the asset value V_t falls below the default boundary V_d for the first time. The firm enjoys tax benefits but is subject to bankruptcy cost α at default. We denote the tax rate to be τ. Following Leland (1994), the value matching and smooth pasting conditions imply that

$$V_d = \frac{(1-\tau)C}{r}\frac{\xi}{\xi - 1}, \tag{10}$$

where $\xi = -\frac{2r}{\sigma^2}$ is the negative root of the characteristic polynomial.

The equity value can be expressed as

$$E = V - \frac{(1-\tau)C}{r} + \left(\frac{(1-\tau)C}{r} - V_d\right)\left(\frac{V}{V_d}\right)^{\xi} \tag{11}$$

where the first part $V - \frac{(1-\tau)C}{r}$ is the firm value net of the debt value with additional tax benefits from the debt, had there been no default. $\left(\frac{V}{V_d}\right)^{\xi}$ is the Arrow Debreu price of default. The second part of the equation can be interpreted as the payoff received by the equity holder at default. It loses the firm value V_d but is no longer required to pay for the debt $\frac{(1-\tau)C}{r}$ at default.

Applying Ito's lemma to the asset dynamic, we can express the equity risk premium as

$$ERP_t = \frac{\partial E_t}{\partial V_t}\frac{V_t}{E_t}\sigma\lambda. \tag{12}$$

Equation (12) shows that the equity risk premium can be decomposed into equity beta and asset risk premium. The equity beta can be further expressed as the interaction between the equity delta and leverage effect. On the one hand, when equity delta is high, the equity is more correlated with the firm's risk, indicating a high equity beta. On the other hand, when leverage is large, the equity value is small and it becomes riskier, leading to a high equity beta.

Next, we derive the credit spread expression. Under the assumption that the creditor get a fraction of the price of the equivalent remaining maturity Treasury at default ("Reovery of Treasury"), the price of a zero coupon bond with τ maturity can be expressed as

$$\begin{aligned} B_{t,\tau} &= e^{-r\tau Q}[\mathbb{I}_{V_\tau > F} + \mathbb{I}_{V_\tau < F}(1-L)] \\ &= e^{-r\tau}(1 - L\pi^Q_{t,\tau}), \end{aligned} \tag{13}$$

where L is the loss given default which is assumed to be constant, and $\pi^Q_{t,\tau}$ denotes the risk neutral default probability. Therefore, the credit spread of this bond can be expressed as

$$s_{t,\tau} = -\frac{1}{\tau}\log(1 - L\pi^Q_{t,\tau}). \tag{14}$$

Based on reflection principle, we have the following lemma:

Lemma 1. *Suppose $F(T) = \Pr(\tau < T)$, where $\tau \in \inf\{t \geqslant 0 : W_t + mt = b\}$ with $m > 0$ and $b < 0$,*

$$F(T) = e^{2mb}N(\frac{b}{\sqrt{\tau}} + m\sqrt{\tau}) + N(\frac{b}{\sqrt{\tau}} - m\sqrt{\tau}), \tag{15}$$

where $N(\cdot)$ denotes the standard normal cumulative distribution function.

According to Lemma 1, $\pi^Q_{t,\tau}$ can be expressed as

$$\pi^Q_{t,\tau} = e^{2mb}N(\frac{b}{\sqrt{\tau}} + m\sqrt{\tau}) + N(\frac{b}{\sqrt{\tau}} - m\sqrt{\tau}), \tag{16}$$

where $m = \frac{r - \frac{\sigma^2}{2}}{\sigma}$, and $b = \log\left(\frac{V_d}{V}\right)/\sigma$.

E Numerical analysis procedure

We first set the initial parameters for high and low credit quality firms based on Table 13. For both high and low credit quality firms, the initial asset value is set to be 100. We also set risk free rate to be 0.02, tax rate to be 0.15, and bankcrupcy cost to be 0.15. For the high (low) credit quality firm, we set the 5-year bond yield to be 0.025 (0.09), sharpe ratio 0.2 (0.08), and loss given default 0.45 (0.55).

Next, based on these parameters, we vary the credit spread slope within the range of $[0.006, 0.008]$, and back out the default boundary and asset volatility the firm based on the Leland (1994) model. Note that the credit spread level and slope moments offer two equations for 2 unknowns, namely asset volatility and default boundary.

Once we obtain the coupon value, we can then compute the equity value, equity beta, and equity risk premium, etc.

We follow the same procedure to conduct the comparative statics for the Merton model.

F Simulation procedure

We set the initial asset value, risk free rate, loss given default, tax rate, bankcrupcy cost, and sharpe ratio to be 100, 0.02, 0.5, 0.15, 0.15, and 0.14, respectively.

We construct a sample of firms with asset volatility taken from 30 evenly spaced numbers over $[0.2, 0.4]$, and default boundary taken from 30 evenly spaced numbers over $[10, 70]$. In particular, we construct firms with all the combinations between the 30 volatility values and 30 default boundary values. Hence, there are 900 firms in total.

Based on the total asset volatility, market sharpe ratio λ_M, and the firm i's sharpe ratio λ_i, we compute the systematic and idiosyncratic volatility as $\sigma_{sym} = \frac{\sigma_{total}\lambda_i}{\lambda_M}$, and $\sigma_{idio} = \sqrt{\sigma_{total}^2 - \sigma_{sym}^2}$. Based on the default boundary value, we obtain the coupon value as $V_d \frac{r(\xi-1)}{(1-\tau)\xi}$.

Next, we simulate 10 years of daily data. We set 360 days for a year, and 30 days each month, for simplicity. For each date, we update the newest firm value according to Equation (9). We then compute the equity value, and credit spreads based on the new firm value. The formula for the equity value is shown as Equation (11), and the formula for the credit spreads is shown as Equation (14).

Once we have the simulated 10-year daily panel data, we pick the month end value to form a sample at the monthly frequency. We compute the one month ahead equity returns based on the equity values and winsorize them at 2.5%, and 97.5% levels.

G Leland (1994) model simulation data summary statistics

Table A3: Descriptive Statistics.

This table presents the cross-sectional descriptive statistics. We first compute the unconditional averages of the variables for each firm. We then generate the cross-sectional summary statistics of the credit spreads (CS), credit spread slope, defined as 10-year credit spreads minus 1-year credit spreads, equity returns, leverage, equity volatility. The data period ranges from January 2001 until March 2018. The data frequency is monthly. Sources: CRSP, Compustat, Markit, and authors' computations.

	obs.	#firms	mean	std	min	25%	50%	75%	max
1y-CS	86494	1068	0.018	0.033	0.000	0.000	0.003	0.021	0.189
5y-CS	86494	1068	0.022	0.023	0.000	0.003	0.015	0.036	0.090
10y-CS	86494	1068	0.019	0.014	0.001	0.007	0.017	0.030	0.054
Slope	86494	1068	0.001	0.023	-0.135	0.002	0.007	0.012	0.025
Equity Return	86494	1068	0.021	0.043	-0.339	0.009	0.021	0.033	0.390
Leverage	86494	1068	0.697	0.189	0.250	0.539	0.728	0.861	0.982
Equity Volatility	86494	1068	0.735	0.356	0.237	0.469	0.634	0.900	2.364

H Double-sort risk premium based on the simulated sample

Figure A2: Returns on stock portfolios sorted by credit spread level and credit spread slope (Simulated data).

In this figure, we report the stock portfolio risk premium sorted by the credit spread level and slope based on the Leland (1994) model simulated sample. We perform the double sort exercise only at the inception of the data. We first sort the stocks based on the 5-year credit spread level into terciles. At each tercile, we then sort the stocks based on the credit spread slope, defined as 10-year credit spreads minus 1-year credit spreads, into five quintiles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. The data is at monthly frequency and the data period is 10 years. Sources: Authors' computation.