The Debt-Equity Spread*

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Abstract

We propose a measure of valuation gap between debt and equity, the debt-equity spread (DES), based on the difference between actual and equity-implied credit spreads. DES predicts the cross section of stock and bond returns in opposite directions, with stronger results among smaller, less liquid, and more difficult-to-short stocks and bonds, and the predictability cannot be explained by exposures to a variety of risk factors. Furthermore, high-DES firms tend to have more negative growth forecast revisions, are more likely to issue equity and retire debt, and have more insider equity selling. These findings on asset pricing dynamics and corporate financing behavior are consistent with DES capturing relative mispricing between debt and equity. They imply that segmentation between the two markets is prevalent at firm level.

JEL classification: G13, G31, G32, G33.
Keywords: credit risk, market segmentation, stock and bond return predictions, relative mispricing

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1 Introduction

Market segmentation has profound implications for finance. When markets are not fully integrated, asset prices in different markets can become disconnected following local shocks, and the asset price dynamics become dependent on the balance sheet conditions of financial intermediaries (see for example Gromb and Vayanos, 2002; Duffie, 2010; Greenwood et al., 2018). Moreover, corporations will adjust their financial policies in response to supply effects in disconnected markets (see for example Stein, 1996; Baker and Wurgler, 2000). As Baker (2009) points out, "there is no crisp delineation between corporate finance and asset pricing" anymore. However, despite its significance, there is limited evidence on how integrated two of the largest markets for corporate financing, the markets of stocks and corporate bonds, actually are, especially on a granular level.[1]

In this paper, we propose to answer this question by systematically measuring the valuation gap between a firm's debt and equity. Since market segmentation is a necessary condition for valuation gaps between debt and equity to exist and persist, one can infer the degree of market segmentation based on how pronounced the valuation gaps are. To verify that our measure indeed reflects valuation gaps between debt and equity, we show that it predicts the cross section of stock and bond returns, as well as corporate financing activities, in ways that are consistent with theories of market segmentation. Moreover, the return predictability is quite persistent, especially for stock returns, and it is stronger among stocks and bonds facing more severe arbitrage frictions. These findings suggest that segmentation between debt and equity markets is prevalent at firm level.

In order to identify the valuation gap between debt and equity, we need to properly account for the distinct cash-flows and risk profiles for equity and debt claims. Our measure, the debt-equity spread (DES), is the difference between two credit spreads:

$$\text{DES} = \text{actual credit spread} - \text{equity-implied credit spread}.$$

The actual credit spread is implied by observed bond prices, while the equity-implied credit spread is calculated using equity market information through the lens of a standard structural credit risk model. When a firm's equity is valued highly relative to its debt, the equity-implied credit spread tends to be low relative to the actual bond spread, resulting in a high DES. Similarly, a low equity valuation relative to debt results in a low DES.

The conversion of equity value into model-implied credit spreads is a necessary step

[1] Previous studies have shown that arbitrages across the two markets (known as capital structure arbitrages) are quite risky overall (Yu, 2006; Duarte et al., 2007). Anecdotally, institutional portfolio managers tend to specialize in one of the two markets.

to facilitate the comparison between debt and equity valuations when firms differ in, for example, leverage ratios, asset volatilities, and debt maturities. This practice is similar to comparing option valuations at different maturities or strikes by converting option prices into implied volatilities using a structural model, such as that of Black and Scholes (1973). We adopt and extend an industry-standard CreditGrades model for this purpose.[2] The standard CreditGrades model is based on Black and Cox (1976) and adds the additional feature of an uncertain default boundary to enhance the model's ability to price shorter maturity debt. The key inputs of the model include the market value of equity, financial leverage, stock return volatility, and bond-level information (e.g., coupon schedule and maturity). We extend this model by incorporating firm-level heterogeneity in payout ratios and derive an exact solution for the extended model.[3]

Since the DES measure is model-dependent, one might suspect that it could be entirely driven by model misspecification, for example, the failure to account for the liquidity component in credit spreads, credit risk premia, or differences in recovery rates across firms conditional on default. While DES is quite likely "contaminated" by these factors, it suffices for our purpose to show that it does capture the relative mispricing between debt and equity. To do so, we examine how the DES measure is linked to (1) the cross section of stock and bond returns, (2) analysts' long-term growth forecasts, (3) corporate financing decisions, and (4) insider trading patterns. On all four dimensions, our findings are consistent with DES containing important information about the valuation gap between debt and equity.

First, we study the predictive power of DES for the cross section of stock and bond returns. This is a test of the predictions of Greenwood et al. (2018). According to their model, when capital moves slowly and there is segmentation between markets of closely related assets, following a local non-fundamental shock, prices will initially overreact in the directly affected market and underreact in the indirectly affected market. This leads to return predictability in the opposite directions in the two markets. Indeed, in the U.S. markets from January 1980 to December 2020, we find that DES negatively predicts the cross section of stock returns, while positively predicting the cross section of corporate bond returns. When sorting stocks monthly into quintiles based on firm-level DES, stocks in the top DES quintile have an average value-weighted excess return of 4.57% (annualized) in the following month, compared to 12.29% for those in the bottom DES quintile. The average value-weighted (equal-weighted) return spread between the bottom and top quintile is 7.72% (7.93%) per

[2]The CreditGrades model was jointly developed by RiskMetrics, JP Morgan, Goldman Sachs, and Deutsche Bank. See Finger et al. (2002).

[3]To obtain an approximate solution, the original CreditGrades model restricts firm value to have zero expected growth under the risk-neutral measure.

year with a t-statistic of 4.29 (4.33). Meanwhile, bonds in the top DES quintile outperform those in the bottom quintile by 4.97% (6.35%) per year with a t-statistic of 5.41 (6.37) for the value-weighted (equal-weighted) portfolios. These results are robust to various controls of standard return factors as well as firm, equity, and bond characteristics. Furthermore, the DES measure is highly persistent. Its stock return predictive power persists for up to five years, whereas its bond return predictive power is relatively shorter-lived. These findings imply the prevalence of market segmentation that persistently hinders cross-market arbitrage.

The opposite direction in which DES is linked to future stock versus bond returns presents a challenge for risk-based explanations. It rules out a variety of risk factors to which the stocks and bonds of the same firm are expected to be exposed in the same direction. We test several potential risk-based explanations that can plausibly generate risk exposures for stocks and bonds in the opposite directions. Specifically, we examine the exposure of DES portfolios to i) realized and implied systematic volatility shocks, ii) shocks to a common component of idiosyncratic volatility (Herskovic et al., 2016), iii) aggregate jump risk, iv) investment-specific technology shocks (Kogan and Papanikolaou, 2014), and v) shocks to government bond yields. The first four alternative explanations are based on the idea that equity holders effectively long a call option on the firm and benefit more from future growth opportunities, while debt holders short a put option on the firm. The time-series regression tests and patterns of factor loadings show that the DES-sorted bond and stock return spreads are unlikely to be driven by these risk factors.

To further distinguish relative mispricing from model misspecification or risk-based explanations, we examine the cross-sectional variation in the predictive power of the DES measure for stock and bond returns. Relative mispricing is likely to be more pronounced among securities that face severe arbitrage frictions. For this reason, we expect that the predictive power of DES for both stock and bond returns to be increasing in a variety of proxies for limits to arbitrage. Consistent with this prediction, DES stock return spreads are substantially wider among stocks that have lower market capitalization, are less liquid (based on dollar volume or the Amihud's measure of illiquidity, Amihud, 2002), are more costly to short (having higher equity lending fees), are more risky to short (based on longer days-to-cover), or have wider analyst forecast dispersion. Similarly, DES bond return spreads are wider among bonds with smaller size, lower dollar volume, lower number of trading days, larger Amihud's illiquidity, and larger gamma (the autocovariance-based illiquidity measure proposed by Bao et al., 2011).

If DES is entirely driven by the structural model's failure to account for the liquidity component in credit spreads, then its ability to predict returns must also be due to the liquidity components in spreads. However, we show that DES's predictive power for stock returns actually becomes stronger among firms that have more liquid bonds, for which the liquidity component ought to be less important. A natural explanation of this finding is that the prices of more liquid bonds are less affected by (bond-market-specific) liquidity factors, which makes them more informative benchmarks to measure potential mispricing in equity. Once again, this finding demonstrates that DES is unlikely to merely reflect model misspecification but rather contains important information about the valuation gap between debt and equity.

After return predictability, we next examine the relation between DES and analysts' long-term earnings growth forecasts. Although high-DES stocks tend to have higher long-term growth forecasts than low-DES stocks *contemporaneously*, we find that DES negatively predicts changes in earnings growth forecasts from year 2 through year 5 in the future. These results suggest that equity analysts are likely overly optimistic about the growth prospects of high-DES firms, which could be a source of the local non-fundamental shocks that generate the valuation gap between debt and equity and lead to subsequent low stock returns. It is worth emphasizing that market segmentation is needed for our DES measure to capture such overoptimism in the equity markets. If the stock and bond market are well integrated, the overoptimistic sentiment in the stock market will also be reflected in bond prices, and there will be no valuation gap according to the DES measure.

As predicted by Stein (1996) and Ma (2019), if there is relative mispricing between debt and equity in segmented markets, corporations are in good positions to take advantage of the arbitrage opportunities. We find strong empirical support for this hypothesis. Firms with higher DES are more likely to issue equity and retire debt. They also tend to draw down cash holdings to fund the debt retirement. The finding of high-DES firms issuing equity and retiring debt in the same quarter confirms and strengthens that of Ma (2019), who uses equity valuation ratios and credit spreads to separately proxy for potential misvaluation of equity and debt. Theoretically, it is the relative mispricing between debt and equity that drives corporate arbitrage behavior; if both equity and debt are mispriced in the same direction, the firm will not necessarily swap one for the other. This is exactly what the DES measure is designed to capture by directly comparing the valuation of debt and equity of the same firm. These findings suggest that potential valuation gaps between debt and equity should be an important consideration in studies of corporate financing decisions.

Finally, we also find that top executives of high DES firms are more likely to sell their stocks in subsequent months relative to those of low-DES firms. These behaviors of corporate managers and insiders provide additional support for DES as a measure of the valuation gap between debt and equity markets.

Related Literature Our study contributes to the literature on the integration/segmentation between equity and credit markets. Earlier contributions include Collin-Dufresn et al. (2001), Longstaff et al. (2005), Schaefer and Strebulaev (2008), Kapadia and Pu (2012), Friewald et al. (2014), and Culp et al. (2018), among others. As evidence for market integration, Schaefer and Strebulaev (2008) show that hedge ratios from the simple credit risk model of Merton (1974) are helpful in explaining the comovements between equity and bond returns. Choi and Kim (2018) also use hedge ratios to examine the integration between the equity and bond markets in the cross section and find mixed evidence across different asset pricing anomalies. Kapadia and Pu (2012) use comovements in daily changes of CDS spreads and stock prices to measure short-horizon pricing discrepancies between CDS and equity markets and find them common in the data. More recently, Sandulescu (2021) constructs a measure of integration between debt and equity markets based on the size of cross-market pricing errors of portfolio-based stochastic discount factors. She finds a nontrivial but imperfect integration between the two markets. Different from these studies, which are all effectively based on comovements in *price changes* or returns of debt and equity, our DES measure is based on the gap in *price levels* and can identify the direction of relative mispricing between debt and equity, which is needed for examining predictions for asset price dynamics and corporate financing behavior.

Our DES measure builds on the idea of capital structure arbitrage, where traders compare credit spreads implied by structural credit risk models against the actual spreads of credit default swaps or corporate bonds to identify arbitrage opportunities. The work by Yu (2006) is among the first to systematically examine the profitability of capital structure arbitrage. Using a CDS sample with 261 firms from 2001 to 2004, he finds that strategies that exploit the mispricing between equity and CDS entail significant risks at the firm level, whereas the portfolio-level tests produce statistically insignificant excess returns because of their limited sample size. Duarte et al. (2007) find that the initial capital required for a capital structure arbitrage strategy is several times higher than for other fixed-income arbitrage strategies. Focusing on corporate bonds instead of CDS allows us to significantly expand the sample in both the time series and cross section. Moreover, we examine the information content of DES on market segmentation more broadly, not just arbitrage profitability. Other papers that use Merton model to facilitate the comparison between debt and equity include van Zundert and Driessen (2022), who find that the corporate bond-implied expected stock returns negatively predict actual stock returns, and Bao and Pan (2013), who find that empirical volatilities of corporate bond and CDS returns are higher than implied by equity volatility.

As a relative mispricing measure between debt and equity, DES offers a few unique features compared to other mispricing measures in the literature. DES is economically motivated and identifies the valuation gap between equity and debt through the lens of a structural credit risk model. In particular, we demonstrate that our model-based DES measure cannot be replicated by a linear combination of the model inputs, which highlights the significance of the nonlinearity as captured by the structural model. Therefore, the DES measure complements existing equity mispricing measures, such as the valuation ratio (see e.g., Dong et al., 2012), the MispScore of Stambaugh et al. (2012), which combines several well-documented anomalies in the stock market, or the firm-level sentiment measures based on textual analysis (see e.g., Ke et al., 2019), where firm-level sentiment scores tend to predict returns at a much higher frequency (for a few days) than DES. In particular, to the extent that equity valuation is more sensitive to firms' growth options while bond valuation is more sensitive to assets in place and downside risks, DES could be viewed as an alternative value measure that uses bond prices as a market-based benchmark to replace accounting-based benchmarks such as book equity or earnings. One distinct feature of DES as a relative mispricing measure is the persistence of predictability, which is important for its influence on corporate financing and insider trading behaviors.

Our paper also contributes to the literature on the implications of market segmentation for asset returns. We draw predictions of market segmentation for asset pricing dynamics from the works of Gromb and Vayanos (2002); Duffie (2010); Greenwood et al. (2018). In a model with partial market segmentation and slow-moving capital, Greenwood et al. (2018) show that when one market is hit with a supply shock, prices of risk in that market become disconnected from prices in other related markets. Moreover, prices in directly and indirectly affected markets can initially overreact and underreact, respectively, resulting in return predictability in opposite directions in the two markets.

Finally, our work contributes to the literature on capital market-driven corporate finance. Baker (2009) surveys earlier work on this topic. More recently, Dong et al. (2012) adopt the discounted cash flow method to show that equity issuance and total financing increase with equity overvaluation. Baker et al. (2020) argue that firms should respond to the Beta anomaly in the equity market by adjusting their leverage ratios. Ma (2019) shows that corporate financing flows are often negatively correlated in the equity and debt markets, and simultaneous issuance in one market and repurchases in the other is common across firms. She argues that these findings can be explained by firms acting as cross-market arbitrageurs. Our work strengthens her finding by directly measuring the valuation gap between the stock and bond of the same firm, which should more accurately identify cross-market arbitrage opportunities for corporations.

The paper proceeds as follows. In Section 2, we describe the construction of DES. In Section 3, we study the implications of DES for cross-sectional stock and bond returns. We also attempt to differentiate the risk-based and mispricing interpretations of the return predictability. In Section 4, we validate our relative mispricing measure via future corporate security issuance and insider trading. We conclude in Section 5.

2 Measuring the debt-equity spread

In this section, we present the CreditGrades model and describe how we construct the debt-equity spread (DES) to assess the valuation gap between the equity and debt markets.

2.1 The extended CreditGrades model

The CreditGrades model is an industry benchmark for credit risk models. It is relatively transparent and easy to implement.[4] We extend the original CreditGrades model by allowing for nonzero growth rates and heterogeneity in the payout ratio, δ. Under the risk-neutral measure, the dynamics of the asset value, V_t, of a solvent firm evolve as follows:

$$\frac{dV_t}{V_t} = (r - \delta)dt + \sigma dW_t, \tag{1}$$

where r is the risk-free rate, δ is the firm-level payout ratio, σ is asset volatility, and W_t is a standard Brownian motion. The heterogeneous payout rate and risk-neutral growth rate, $r - \delta$, further increases the average credit spread as a result of its convex relation with default risks (Feldhütter and Schaefer, 2018).

The total face value of the firm's debt is D. Default is triggered when the asset value V_t declines to the firm-specific random default boundary $L \times D$, where

$$L = \overline{L}e^{\lambda Z - \lambda^2/2}, \quad Z \sim N(0, 1), \tag{2}$$

[4] The CreditGrades model is derived from the seminal Black and Cox (1976) model but differs in two perspectives: i) it assumes a zero growth rate of the underlying firm values, and ii) it introduces uncertainty about the default boundary. In particular, the introduction of an uncertain about the default boundary alleviates the well-known "credit risk puzzle" (See Jones et al. (1984) and Huang and Huang (2012)). Recent developments in this literature incorporate various ingredients to resolve this puzzle, such as the market risk premium, time-varying volatility, jump risks, investment options, countercyclical bankruptcy costs, and illiquidity (Almeida and Philippon, 2007; Chen et al., 2009; Chen, 2010; Bhamra et al., 2010; Kuehn and Schmid, 2014; Du et al., 2019; Gomes and Schmid, 2021; Longstaff et al., 2005; Chen et al., 2018). However, whether a simple model like Black and Cox (1976) is able to account for the empirical credit spread is still under debate (Chen et al., 2009; Feldhütter and Schaefer, 2018; Bai et al., 2020).

and Z is independent of W_t. Thus, $\mathbf{E}(L) = \overline{L}$ and $\mathbf{var}(L) = \lambda^2$. Notice that the presence of a stochastic default boundary makes the timing of default unpredictable. Intuitively, at any asset value, there is a finite probability that default can occur instantaneously when Z is sufficiently large. This notion is similar in spirit to Duffie and Lando (2001), who introduce uncertainty about the value of firm assets resulting from incomplete accounting information. Without the stochastic default boundary (i.e., $\lambda = 0$), the model collapses to the standard Black-Cox model.[5] For an initial asset value V_0, default does not occur as long as

$$V_0 e^{\sigma W_t + (r-\delta-\sigma^2/2)t} > \overline{L} D e^{\lambda Z - \lambda^2/2}. \tag{3}$$

2.2 Bond pricing

Accordingly, in this extended CreditGrades model, the price of a T-period coupon bond with annual coupon rate c and face value \$1 is

$$D_0(T) = E_0^Q \left[\int_0^T e^{-\int_0^s r_u du} c 1_{\{\tau > s\}} ds + e^{-\int_0^T r_u du} 1_{\{\tau > T\}} + \int_0^T e^{-\int_0^s r_u du} L \, 1_{\{\tau = s\}} ds \right]. \tag{4}$$

With discrete (quarterly) coupon payments c, the above equation becomes

$$D_0(T) = \sum_s P_0(s) q(s) c + P_0(T) q(T) - \int_0^T P_0(s) q'(s) \overline{L} ds, \tag{5}$$

where $P_0(s)$ is the price of a riskless zero-coupon bond with maturity s at time 0, $q(t)$ is the unconditional survival probability, and $q'(t)$ is its first-order differentiation with respect to time.

The unconditional survival probability $q(t)$ is given by[6]

$$q(t) = \int_{-\infty}^{\overline{Z}} q(t|z) d\Phi(z), \tag{6}$$

with the upper bound

$$\overline{Z} = \frac{\lambda}{2} - \frac{1}{\lambda} \log\left(\frac{\overline{L}D}{V_0}\right). \tag{7}$$

[5] Our results are robust to different model specifications when applying the Black-Cox model in the Internet Appendix B.2.

[6] Equation (6) can be further expressed in terms of the cumulative distribution functions of bivariate normal distributions.

The conditional survival probability, q(t|z), is as follows:[7,8]

$$q(t|z) = \Phi\left(\underbrace{C \cdot \sigma\sqrt{t} - \frac{y}{\sigma\sqrt{t}}}_{\text{Distance to default}}\right) - e^{2Cy}\Phi\left(C \cdot \sigma\sqrt{t} + \frac{y}{\sigma\sqrt{t}}\right), \tag{10}$$

where $\Phi(\cdot)$ is the cumulative normal distribution function, and

$$C = \frac{r-\delta}{\sigma^2} - \frac{1}{2}, \tag{11a}$$

$$y = -\log\left(\frac{V_0}{\overline{L}D}\right) - \frac{\lambda^2}{2} + \lambda z. \tag{11b}$$

Intuitively, the conditional survival probability, $q(t|z)$, in equation (10), increases with the distance to default in equation (11b). A higher asset value V_0 implies a longer distance to default, a higher survival probability, and consequently a greater valuation of bonds in equation (5).

2.3 Empirical implementation

We obtain monthly observations of corporate bond prices from three data sources: Lehman Brothers Fixed Income Database, TRACE, and Mergent FISD/NAIC.

Lehman Brothers Fixed Income Database provides month-end bid prices from 1973 to 1998. Since Lehman Brothers used these prices to construct the Lehman Brothers bond index while trading on it, the traders at Lehman Brothers had the incentive to provide correct quotes. Thus, although the prices in the Lehman Brothers Fixed Income Database are quote based, they are generally considered reliable. However, we exclude matrix prices, which are set using algorithms based on the quoted prices of other bonds with similar characteristics.

[7]For a drifted Brownian motion $Y_t = at + bW_t$ with constant drift coefficient a and diffusion coefficient b, and $Y_0 = 0 > y$ (see, e.g., Harrison, 1985),

$$\mathbb{P}\{Y_s > y, \forall s < t\} = \Phi\left(\frac{at-y}{\sigma\sqrt{t}}\right) - e^{2ay/\sigma^2}\Phi\left(\frac{at+y}{\sigma\sqrt{t}}\right). \tag{8}$$

We obtain the conditional probability, $q(t|z)$, by setting $a = (r - \delta - \frac{\sigma^2}{2})$ and $b = \sigma$.

[8]A simple algebraic calculation gives us the following first-order differentiation of conditional survival probability $q(t|z)$:

$$q'(t|z) = \phi\left(\frac{C \cdot \sigma^2 t - y}{\sigma\sqrt{t}}\right)\left(C \cdot \frac{\sigma^2}{2\sigma\sqrt{t}} + \frac{y\sigma^2}{2(\sigma\sqrt{t})^3}\right) - e^{2Cy}\phi\left(\frac{C \cdot \sigma^2 t + y}{\sigma\sqrt{t}}\right)\left(C \cdot \frac{\sigma^2}{2\sigma\sqrt{t}} - \frac{y\sigma^2}{2(\sigma\sqrt{t})^3}\right). \tag{9}$$

The data from Mergent FISD/NAIC and TRACE are transaction based. The Mergent FISD/NAIC database consists of actual transaction prices reported by insurance companies from 1994 to 2002. The TRACE data provide actual transaction prices from 2002 to 2020, covering more than 99% of the over-the-counter (OTC) activity in the US corporate bond markets since 2005. Following Bessembinder et al. (2008), we construct the daily bond price by calculating the trading-volume-weighted average of the transaction price.

Because our goal is to measure the valuation gap between the equity and bond markets, we prioritize the datasets based on transaction prices and complement them with quoted prices. Thus, whenever there are duplicates of bond records, we use the priority of TRACE, Mergent FISD/NAIC, and then Lehman Brothers Fixed Income Database.

Following the standard CreditGrades model and setting the current date to time 0, we approximate the market value of firm V_0 as

$$V_0 = S_0 + \overline{L}D, \tag{12}$$

where S_0 is the daily equity value from the Center for Resrach in Security Prices (CRSP), and D is the total liability (data item LT) from Compustat. When calculating S_0, we match the date of the stock price with that for the bond price to ensure that the model-implied bond price and actual bond price are comparable at the same day. As a key input of the model, the market value of equity S_0 has a direct impact on the distance to default and the conditional survival probability. As we have discussed for equation (10), all else being equal, a higher equity value S_0 increases the asset value V_0, the survival probability, and the implied bond valuation.

According to the CreditGrades model, we set the average recovery rate $\overline{L}$ to 0.5 and the volatility of the recovery rate λ in equation (2) to 0.3. Equity volatility σ^S is calculated using daily returns in the past three years up to the end of the previous month to avoid potential look-ahead bias. To estimate the asset volatility, we follow Feldhütter and Schaefer (2018) and first calculate $\sigma = \sigma^S(1 - R_0)$, where $R_0 = D/(S_0 + D)$, and then adjust σ by a factor of 1 if $R_0 < 0.25$, 1.05 if $0.25 < R_0 \leq 0.35$, 1.10 if $0.35 < R_0 \leq 0.45$, 1.20 if $0.45 < R_0 \leq 0.55$, 1.40 if $0.55 < R_0 \leq 0.75$, and 1.80 if $R_0 > 0.75$. We adopt this adjustment because it is transparent and easy to replicate. It also avoids a potential problem from the standard deleveraging procedure that gives rise to unreasonably small asset volatilities for highly distressed and leveraged firms.

To calculate the bond value in equation (5), we interpolate, in a six-month interval, the yield curve of zero-coupon bonds obtained from the Federal Reserve Bank of St. Louis Economic Data (FRED) website. Deviating from the standard CreditGrades model, we follow Feldhütter and Schaefer (2018) and Bai et al. (2020) and calculate the payout rate as the sum of dividends, interest expenses, and stock repurchases, divided by the sum of the market value of equity and debt each quarter. The dividend payment is the indicated annual dividend (DVI) from Compustat, multiplied by the number of shares. The indicated annual dividend is updated daily and is adjusted for stock splits and so on. Net stock repurchases are the total repurchases of common and preferred stocks. Stock repurchases and interest expenses are calculated for the past four quarters. If the payout ratio is larger than 0.15, we set it to 0.15. We require a lag of at least two months between the accounting information and the market equity and bond prices.

2.4 The debt-equity spread

With the above inputs, we solve for the theoretical bond price in equation (5) and convert it to the equity-implied credit spread CS^{E}. We follow Gilchrist and Zakrajšek (2012) and calculate the credit spread as the difference between the bond yield and the yield of a hypothetical Treasury security with the same cash flow as the underlying bond. Then, we obtain the difference between the actual spread CS^{D} and the equity-implied spread CS^{E} for each bond, in each month, as our valuation gap measure:

$$\mathrm{DES} = \mathrm{CS}^{\mathrm{D}} - \mathrm{CS}^{\mathrm{E}}. \tag{13}$$

DES potentially measures the degree of equity overpricing relative to debt. If equity investors are more optimistic about the firm's fundamentals than bond investors, stocks are likely to be overpriced. As we have discussed for equation (12) in the model implementation, the inflated stock price implies a high observed asset value and bond prices, which in turn results in a low equity-implied credit spread (CS^{E}) and high DES. In contrast, if the stock price is relatively undervalued, we observe a high implied credit spread and low DES.

We aggregate bond-level (actual and implied) credit spreads and DES to the firm level. That is, we calculate the value-weighted average of credit spreads and DES for all the bonds of the same firm, using the weight of bond size, in an effort to mitigate the liquidity concern.

To assess the model performance, we sort firms into five quintile portfolios based on actual firm-level credit spread, and then calculate the value-weighted average of equity-implied credit spreads with the weight of equity size. Panel A of Figure 1 shows that the equity-implied credit spreads generally align well with their actual counterparts, with a correlation coefficient of 75%, although the extended CreditGrades model tends to underestimate the actual credit spreads when they are above 1,800 basis points. Panel B illustrates the histogram of differences between the actual and implied credit spreads, which is essentially our DES measure, at the portfolio level. DES ranges from less than −400 basis points to 800 basis points. Furthermore, DES is in general close to be normally distributed with a mean of 25.17 basis points and is slightly right skewed.[9] The average difference, or DES, between actual and implied credit spreads is reasonably small. As a robustness test, we also implement the Black-Cox model and show our results are robust to model choices in Section B.2 of Internet Appendix.

[Insert Figure 1 here]

Despite the close fit between model-implied and actual credit spreads on average,[10] it is worth emphasizing that the average level of DES is not the focus of our study. For example, model-implied credit spreads according to the CreditGrades model could be on average lower than the actual bond spreads to due to missing the liquidity effects. Instead, to validate that DES indeed captures the relative mispricing between debt and equity, we focus on how DES is connected to asset price dynamics and corporate financing behavior.

In Figure 2, we plot the time series of the distribution of the firm-level DES, including its median, 25th percentile, and 75th percentile. The median DES is relatively smooth and does not strongly comove with business cycles. Furthermore, the cross-sectional dispersion tends to increase around recessions, as is evident from the recessions in 1991, 2001, and, more recently, the 2008 Great Recession.

[Insert Figure 2 here]

In the following sections, we use the bond-level DES to evaluate the cross-sectional bond return prediction and firm-level DES to assess the cross-sectional stock return prediction and corporate activities.

3 DES and asset prices

In this section, we study the asset pricing implications of DES. As predicted by Greenwood et al. (2018), when markets of closely linked assets are (partially) segmented, non-fundamental shocks in one market can make prices in related markets become disconnected for extended

[9] In an untabulated analysis, we find the match between the actual and equity-implied credit spreads is noisier at the bond level, with an average bond-level DES of about 70 basis points, implying that model-implied credit spreads undershoot those in the data.

[10] This result does not contradict with the credit spread puzzle (see e.g., Huang and Huang, 2012) because the calibration of the CreditGrades model does not require matching average probability of default and recovery rates under the physical probability measure.

periods. In the presence of segmented markets and slow-moving capital (which could be due to search frictions, arbitrage frictions, or investor inattention; see Duffie, 2010, for more discussion), such local shocks can simultaneously lead to price *underreaction* in the market not directly affected by the shock and price *overreaction* in the directly affected market. The underreaction is due to arbitrageurs slowly incorporating the impact of the shock into indirectly affected markets. The overreaction is because there is limited capital to accommodate the shock in the directly affected market (for example, limited capital to absorb an increase in the supply of stocks, or slow reaction by institutions to accommodate a sudden rise in retail demand). Importantly, Greenwood et al. (2018) show that prices in both markets will overreact in the short run if only slow-moving capital is present (no market segmentation).

In our context, debt and equity of the same firm are close substitutes whose prices should be tightly linked by cross-market arbitrage in the absence of market frictions. With market segmentation and slow-moving capital, either local demand (e.g., fluctuations in retail equity investor sentiment or the sudden divestment of corporate bonds by an institutional investor) or supply effects (e.g., corporate equity or debt issuance) could result in a valuation gap between debt and equity, which our DES measure is designed to capture. Returns of stocks and bonds are expected to move in opposite directions following the local non-fundamental shocks due to the simultaneous under- and overreaction in prices in the two markets, which implies that DES should predict stock and bond returns in opposite direction. Furthermore, since the effects of slow-moving capital are expected to be stronger among stocks and bonds facing more severe arbitrage frictions, we would expect the predictive power of DES to be stronger among these securities. These are the primary predictions about asset price dynamics that we examine in this section.

Next, we describe the data sources and variable definitions in Section 3.1. We examine the cross-sectional relation between DES and future stock and bond returns using portfolios in Section 3.2 and using Fama-MacBeth regressions in Section 3.3. In Section 3.5, we conduct several empirical tests to differentiate mispricing interpretations from risk-based explanations.

3.1 Data and variable definitions

The data used in our analyses come from several sources. Besides the bond data we described in the previous section for constructing DES, we also obtain monthly stock data from the Center for Research in Security Prices (CRSP) database and monthly bond return data from Lehman Brothers Fixed Income Database, NAIC, and Wharton Research Data Services (WRDS), as well as accounting data from the Compustat annual and quarterly databases.

Specifically, we use the monthly bond return from Lehman Brothers Fixed Income Database from January 1980 to March 1998 and calculate bond returns using transaction prices from NAIC from January 1994 to July 2002. Whenever two returns overlap for the same bond, we use the one from NAIC because they are transaction-based. The detailed calculation can be found in Section A.2 of the Internet Appendix. After July 2002, we use RET_L5M from WRDS Bond Return Database to measure monthly bond returns. To ensure there are sufficient stocks in the cross section, we start the asset pricing analyses from 1980, and our benchmark sample includes all NYSE/AMEX/NASDAQ common stocks (excluding stocks in the financial industry) from January 1980 to December 2020. All firm characteristics and control variables used in Section 3 are described in Table 1.

[Insert Table 1 here]

3.2 DES portfolios

We start our analyses of the stock and bond return predictions using the portfolio approach.

3.2.1 Stock portfolios

At the beginning of each month from January 1980 to December 2020, we sort stocks into quintiles based on the firm-level DES. These portfolios are held for one month before rebalancing at the beginning of the next month.

Table 2 reports summary statistics of the characteristics of these portfolios. Panel A examines the relation between DES and its input variables in the extended CreditGrades model. Because of the data availability of corporate bond prices, each portfolio has around 67 stocks per month on average. The average DES is −61.64 basis points in the lowest DES quintile and 251.69 basis points in the highest DES quintile. The cross-sectional difference in DES is driven by both CS^{D} and CS^{E}, as both display a U shape across DES quintiles. The increasing DES and the U-shaped actual credit spreads provide the first indication that our DES measure is not driven by default risk. Panel A also shows that high-DES stocks have slightly higher asset volatility, lower financial leverage, and a lower payout rate than low-DES stocks. The relation between DES and bond maturity (and duration) is nonmonotonic, which suggests that differentials in the interest rate risk exposure are unlikely to explain the bond DES premium we discuss below.

[Insert Table 2 here]

Panel B of Table 2 reports the means of several other stock, bond, and firm characteristics for firms in the DES quintiles. The relations between DES and most of these characteristics are weak and display either a U shape or a hump shape across quintiles. Compared with those in the bottom DES quintile, firms in the top DES quintile tend to have smaller market capitalization, a lower book-to-market ratio, and higher gross profitability.

[Insert Table 3 here]

Table 3 reports the average returns and abnormal returns from the CAPM, the Fama and French (1992) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, the Stambaugh and Yuan (2017) mispricing factor model, and the Hou et al. (2015) q-factor model (HXZ) for the DES quintile portfolios. We report the results using both the value-weighted (VW) scheme and equal-weighted (EW) scheme. Panel A shows that stocks with a high DES have an average VW return of 4.57% per year, lower than the 12.29% for stocks with a low DES. The return spread between these two quintiles (L-H) is 7.72% per year with a *t*-statistic of 4.29. This DES premium cannot be explained by the aforementioned asset pricing models. The abnormal returns remain more than 6% per year and are statistically significant when controlling for these factors. Importantly, the alpha for the long-short portfolio in the Stambaugh and Yuan (2017) mispricing factor model test is 7.09% per year indicating that DES contains very different information from the two mispricing factors in Stambaugh and Yuan (2017).

As reported Panel A of Table 3, the results from equally weighted portfolios are similar and quantitatively stronger than those of value-weighted portfolios. The average annualized return spread is 7.93% per year, with a *t*-statistic of 4.33. The abnormal returns from the above-mentioned factor model tests are statistically significant.

We illustrate the stock return predictability of DES in the top panel of Figure 3. We plot the cumulative returns of the long-short portfolio, which longs low-DES stocks and short-sells high-DES stocks. The value-weighted strategy produces relatively stable returns. Interestingly, the equally weighted portfolio generates a performance similar to the value-weighted portfolio before 2000 and then starts to outperform. Economically, a \$1 investment in the value-weighted portfolio can be turned into \$17 at the end of the sample period, and the corresponding balance for the equally weighted portfolio is around \$20.[11]

[Insert Figure 3 here]

[11] In Section 3.4 of the Internet Appendix, we explore the long-horizon stock return prediction of DES using buy-and-hold portfolios. We find that DES significantly predicts stock returns even five years following the portfolio rebalancing. This result indicates that if DES measures systematic risk or mispricing, this risk exposure/mispricing should be highly persistent.

3.2.2 Bond portfolios

We report average annualized excess bond returns and alphas in the cross section in Panel B of Table 3. We sort bonds into quintiles based on their bond-level DES of the previous month and calculate the value- and equal-weighted portfolio bond returns. In sharp contrast to equity markets, the average value-weighted bond returns increase with DES, with an annualized return spread of –4.97% (t-statistic = –5.41) for the VW scheme and –6.35% (t-statistic = –6.37) for the EW scheme.

Then, we control for standard factors. When we regress the VW portfolio bond returns on the bond market returns, proxied by the Merrill Lynch index, the bond alpha of the long-short portfolio (L-H) becomes even larger at −5.13% (t-statistic = −5.86) per year. When we control for the four factors proposed by Bai et al. (2019), which include the bond market factor, downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF), the alpha becomes −2.86% (t-statistic = −2.05).[12] We observe quantitatively stronger results when we use the equal-weighted scheme.

We also visualize the bond return predictability of DES in Panel B of Figure 3 by plotting the cumulative returns of the long-short bond portfolio, which simultaneously shorts low-DES bonds and longs high-DES bonds. The performance of the bond DES strategy is stable over the sample period. Economically, a $1 investment in the value-weighted portfolio would generate a payoff of $7.3 at the end of the sample period, and the same investment for the equally weighted portfolio generates a payoff of $12.8.[13]

In summary, we find significant predictive power of DES for the cross section of stocks and bonds in opposite directions. The fact that return predictability is in opposite directions for stocks and bonds are consistent with DES capturing the relative mispricing between equity and debt. They rule out a variety of risk factors to which the stocks and bonds of the same firm are expected to be exposed in the same direction. We test several potential risk-based explanations in Section 3.5.

3.3 Fama-MacBeth regressions

In this section, we run monthly Fama-MacBeth regressions to test the return prediction of DES. While portfolio analyses and asset pricing tests control for standard factor exposure, Fama-MacBeth regressions allow for additional controls of firm and bond characteristics.

[12] The sample period for the four-factor model test only starts in July 2004 because of the data availability of the Bai et al. (2019) factors.

[13] This result is robust to decade-by-decade subsamples in Section B.1 of the Internet Appendix. Our results are also robust to the industry adjustment in Section B.3, CDS trading in Section B.4.

More importantly, we horse-race our DES measure with its model inputs and two main components: actual and implied credit spreads.

3.3.1 Firm-level characteristics

We present results for stock returns in Panel A of Table 4, where we control for nine conventional firm-level characteristics in Fama-MacBeth regressions. These characteristics include idiosyncratic volatility (Ivol), financial leverage (Mlev), failure probability (FP), logarithm of firm size (logSize), book-to-market equity ratio (BM), momentum (Mom), gross profitability (GP), asset growth (AG), and asset tangibility (Tangibility).

[Insert Table 4 here]

In the univariate regression in the first column of Panel A, the coefficient of DES is -0.16 with a t-statistic of -4.45. Although the inclusion of some other firm characteristics tends to lower the return predictive power of DES, the results in Specifications 2-6 show that the coefficient of DES remains statistically significant. In Specifications 7-8, we also consider MispScore from Stambaugh et al. (2012). Since the data for MispScore end in December 2016, we report the bivariate return predictive regressions using DES and MispScore in Specification 7. Consistent with the findings in Stambaugh et al. (2012), MispScore is a strong and negative predictor for future stock returns. However, the return predictive power of DES remains largely intact when we control for MispScore. In Specification 8, we include all the variables we considered in Specifications 1-7. The coefficient on DES remains negative and statistically significant from zero. Therefore, our results suggest that, although MispScore is a comprehensive measure based on several equity anomalies, our valuation gap measure, DES, contains distinct information about future stock returns. In Specification 9, we control for the lagged 1-month value-weighted bond return, which is aggregated across bonds for each stock. The coefficient on the lagged bond return is insignificant from zero, whereas the coefficient on DES is very close to that in Specification 6. This result indicates that the DES return prediction is not driven by prior bond returns.

In Panel B, we report the results for bonds. In the univariate regression in Specification 1, the estimated coefficient of DES is 0.13 with a t-statistic of 5.2, which confirms the portfolio results from Panel B of Table 3. The DES coefficient remains economically and statistically significant in Specifications 2 to 4, where we introduce firm characteristics described in Panel A, Table 4. The positive coefficient on market leverage reflects the greater default risk associated with higher leverage. In Specification 5 where we control for bond characteristics, including the logarithm of bond size (logBondSize), amount outstanding (Amount), bond age

(Age), coupon rate (Coupon), and bond maturity (Maturity), the DES coefficient remains at 0.12 (t-statistic = 5.13). Among all the bond characteristics, the bond size and amount outstanding show significant predictive power. The results are quantitatively similar when we include both firm and bond characteristics in Specification 6.

Similar to our test for stocks, we also control for MispScore from Stambaugh et al. (2012) for bonds in Specifications 7 and 8. While DES remains a strong, positive return predictor, we find the coefficient on MispScore is negative but statistically insignificant, which is not surprising because it derives from stock return anomalies only. Our DES measure, in contrast, combines the information from both stock and bond markets and could capture the mispricing between the debt and equity of the same underlying assets.

In Specification 9, we include prior 1-month stock returns as a control variable. The literature (see e.g., Kwan (1996) and Chordia et al. (2017)) documents that equity returns lead bond returns, which we confirm in Specification 9: prior 1-month stock returns strongly predict the subsequent 1-month bond return, with a t-statistic of 5.23. However, the positive coefficient of DES is almost unchanged from that in Specification 6, and therefore, the return prediction of DES is beyond the lead-lag relation between stock and bond returns.

3.3.2 CreditGrades model inputs

Our DES measure performs reasonably well using various standard factor models and Fama-MacBeth tests. An intriguing question would be whether and to what extent the predictive power of DES is driven by the (linear combination of) inputs of our extended CreditGrades model.

We address this question in Table 5. In Panel A, we study the separate predictability from individual inputs for stock returns using univariate Fama-MacBeth regressions. These inputs include asset volatility (AVol), leverage ratio (Lev), and payout ratio (Payout). Specifications 2-4 show that asset volatility negatively predicts stock returns, whereas the coefficient on the payout ratio is significantly positive. However, in the horse race regressions between DES and the linear combination of model inputs in Specification 5, DES remains a strong return predictor because its coefficient barely changes from the univariate regression in Specification 1, indicating that a linear combination of model inputs cannot take away the exploratory power of our structural model-based DES measure.

[Insert Table 5 here]

More importantly, we directly compete our DES with its two components, the actual credit spread (CS^D) and implied credit spread (CS^E). A striking finding in Specifications

6 and 8 is that although their difference (DES) can predict future stock returns, neither CS^D or CS^E has a significant coefficient in the Fama-MacBeth regressions. In the bivariate regressions in Specifications 7 and 9, the coefficient of DES remains statistically significant.

In Panel B, we perform the same exercises for bond returns. Besides the firm characteristics from Panel A, we also include bond maturity and an indicator variable for callable bonds in the Fama-MacBeth regressions. Consistent with the literature, the actual credit spread, CS^D, has a positive and significant coefficient for bond returns. However, the coefficient of DES remains economically and statistically significant, implying that the information content of our DES is different from the default risk (or liquidity risk) in the actual credit spread.

Taken together, our results indicate that the opposite predictive power of DES on stocks and bonds does not come from the *linear* combination of individual model inputs or its two main components, such as actual and implied credit spreads. Instead, it is the difference between the actual and implied credit spreads – the valuation gap between equity and debt markets – that contains the unique information about future stock and bond returns in the cross section.

3.4 Persistence of return predictability

In the previous two subsections, we document that DES has opposite predictions for stock and bond returns in the subsequent month. Next, we examine how persistent the return predictability of DES is.

Before discussing the results on long-horizon return forecasting, we first examine the persistence of the DES measure. Figure 4 shows the dynamics of average DES for each of the DES quintiles in the 5 years before and after quintile formation. It shows that DES is mean-reverting but highly persistent. During the 11-year event window, the rankings of the average DES across quintiles never change. By construction, the gap in average DES between the top and bottom quintile peaks at year 0 at about 300 bps. The gap is still nearly 200 bps two years before and after portfolio formation, and at about 100 bps five years before and after formation.

[Insert Figure 4 here]

Next, we examine the monthly average buy-and-hold returns of DES long-short portfolios for stocks and bonds with holding periods ranging from one to 60 months. The results are in Figure 5. The left panel shows that the average stock return starts at 0.64% per month and gradually declines with the holding period. However, the average return remains sizable and statistically significant even five years after portfolio formation. In contrast, the average buy-and-hold bond return in the right panel decays at a faster pace; it loses statistical significance 8 months following the portfolio formation.

[Insert Figure 5 here]

If cross-market arbitrage forces are strong, any valuation gap between stock and bond markets should be closed quickly. The fact that DES predicts the cross section of stock and bond returns for multiple months (up to 5 years in the case of stocks) with no sign of reversal suggests that the valuation gap can be quite persistent, which is evidence for the significance and prevalence of market segmentation. The persistence of predictability by DES is also necessary for it to influence corporate financing and insider trading behaviors, which we examine in Section 4.

3.5 Mispricing or risk exposure

The strong predictive power for stock and bond returns makes it unlikely that DES is simply noise caused by model misspecification. However, it is still possible that its predictability stems from exposures to certain risk factors rather than driven by relative mispricing between debt and equity. In this subsection, we try to distinguish between these two explanations in order to validate DES as a valuation gap measure.

3.5.1 Limits to arbitrage

We first study the role of limits to arbitrage in both stock and bond return predictions by DES. If DES measures the relative mispricing between debt and equity, we would expect the DES premium to be stronger among stocks and bonds facing more severe limits to arbitrage (Shleifer and Vishny, 1997). To examine this prediction, we use sequential double sorts, first sorting stocks or bonds into terciles based on proxies of limits to arbitrage, and then further sorting securities within each tercile into terciles based on DES.

[Insert Table 6 here]

Table 6 reports the stock portfolio returns in double-sorted portfolios. We consider six proxies for limits to arbitrage: equity size, Amihud illiquidity (Amihud, 2002), dollar volume, days-to-cover, equity lending fee, and analyst forecast dispersion. The DES premium is substantially larger among stocks that are less liquid (as proxied by small equity size, high

Amihud illiquidity, and low dollar volume), more risky to short (as proxied by longer days-to-cover), more expensive to short (as proxied by higher equity lending fees), or have more potential disagreement among investors (as proxied by greater analyst forecast dispersion). For example, the DES premium is 7.25% per year for small stocks, as compared with 3.74% for big stocks. Similarly, the DES premium is 13.22% among stocks with high equity lending fees but only 2.91% among stocks with low equity lending fees. The differences conditional on the limits to arbitrage levels remain largely the same after controlling for Carhart four factors.

[Insert Table 7 here]

We then examine bond return predictability in the same manner based on five different proxies for limits to arbitrage, including bond size, Amihud illiquidity, dollar volume, gamma (the autocovariance-based illiquidity measure proposed by Bao et al., 2011), and the number of trading days within each month. The bond size measure is available in the full sample from 1980 to 2020. The remaining four measures are constructed using the transaction data from TRACE from 2002 to 2020. The results are reported in Table 7. Similar to that in stocks, the DES premium is substantially larger among bonds with smaller size, high level of Amihud illiquidity, low dollar volume, high bond gamma, and low number of trading days. For example, the DES premium is −2.13% per year for large bonds, compared to −7.03% for small bonds.

Lastly, we examine whether the predictive power of DES could be driven by a particular form of model misspecification due to bond illiquidity. The CreditGrades model does not capture the effect of illiquidity, which have been shown to be an important component in observed credit spreads (see e.g., Longstaff et al., 2005; Chen et al., 2018, among others). It is possible that firms with higher DES because their bonds are more illiquid. For bond returns, we have already shown that the long-short DES bond portfolio returns have significant alpha after controlling for the four factor model of Bai et al. (2019), which includes a bond liquidity factor (see Panel B of Table 3). Similarly, in the Fama-Macbeth regressions, DES remains significant after controlling for various measures of bond liquidity (see Panel B of Table 4). These results show that the predictive power of DES for bond returns goes beyond bond liquidity.

[Insert Table 8 here]

Similarly, we show that DES's predictive power for stock returns cannot be simply due to its correlation with bond liquidity, either. To do so, we perform a cross-market double-sorting, first sorting firms into terciles based on the liquidity of their bonds (based on the Amihud illiquidity, dollar volume, or number of tradedays), and then sorting on their stocks within each tercile into terciles based on DES. As Table 8 shows, the DES premium actually becomes stronger among firms that have more liquid bonds, for which the liquidity component ought to be less important. A natural explanation of this finding is that the prices of more liquid bonds are less affected by (bond-market-specific) liquidity factors, which makes them more informative benchmarks to measure potential mispricing in equity. Once again, this finding demonstrates that DES is unlikely to merely reflect model misspecification but rather contains important information about the valuation gap between debt and equity.

Notice that our goal is not to show that DES is unaffected by factors such as bond liquidity, which it most likely is. Instead, the point is that it suffices for our purpose to show that DES does capture the relative mispricing between debt and equity, which implies market segmentation. Our extensive tests on DES and limits to arbitrage, as well as the cross-market double-sorting results, provide further support to the "relative mispricing" interpretation of the DES measure.

3.5.2 Risk factor exposures

The opposite movements of excess stock and bond returns, as shown in Section 3.2, cannot be explained by standard linear factor models. However, it is still possible that DES predicts returns as a result of its exposure to other risk factors, which is not captured by standard factor models and might have opposite impacts on stock and bond valuations.

It is well known that equity holders benefit from an unlimited upper side, whereas debt holders bear downside risk because of limited liabilities. The classic model of Merton (1974) formalizes this idea by showing that the put option embedded in equity and debt values has the opposite effects on them because of put-call parity. In the same spirit, compared with debt holders, equity holders are more likely to benefit from growth options and investment shocks (Kogan and Papanikolaou, 2014).[14]

Although the put and growth options are not observable, their values are increasing with increased volatility and jumps, which in turn have opposite effects on equity and debt values. To examine whether an alternative missing factor could explain the opposite movements, we consider three sets of proxies related to the put and growth options and interest rate

[14]Kogan and Papanikolaou (2014) offer a risk-based explanation for the value premium based on asset composition. According to their interpretation, growth stocks have more growth options and have a higher exposure to investment-specific technology shocks relative to value stocks, which derive more value from assets in place. They show that investment shocks carry a negative risk premium, so investors demand higher expected returns for value stocks relative to growth stocks.

risk. The first set includes various proxies for stochastic volatility and jumps, the second set includes aggregate growth opportunities, and the last set is the change in Treasury yields.

In our first attempt, we consider three empirical measures of volatility shocks. The first measure is the shock to the common idiosyncratic volatility from Herskovic et al. (2016) (dCIV)[15] which captures the common movement of idiosyncratic volatility across firms. The second measure is the change in the variance of daily market returns within a month (dMVAR), and the third measure is the change in the VIX index (dVIX). A caveat for the last two measures is that they may also capture the quantity of systematic risk that affects the discount rate. Given the negative risk premium for dCIV in Herskovic et al. (2016) and aggregate volatility risk in Ang et al. (2006), we expect upward-sloping volatility betas to explain the declining stock returns and downward-sloping volatility betas to explain the increasing bond returns.

For each volatility measure, we run time-series regressions of DES portfolio returns on the market factor and volatility shock measure and report the results in Panel A (stocks) and Panel B (bonds) of Table 9. The top three specifications in each panel report the coefficients of volatility shocks. The results show that there is a decreasing pattern in the dCIV and dMVAR betas among stock portfolios, with negative volatility betas in high-DES firms, which is contrary to our expectation and even exacerbates the declining stock DES premiums. For the bond portfolios in Panel B, although the significant volatility betas for the L-H portfolio contribute to the bond DES premium, the general beta pattern is nonmonotonic across the DES quintiles. Therefore, the volatility exposure is unlikely to explain the difference in the stock and bond DES return spreads.

[Insert Table 9 here]

Another related effect on options is the exposure to jump risk.[16] We follow Benzoni et al. (2011) and measure jump risk as the change in the implied volatility of the deep out-of-the-money Standard and Poor's (S&P) 500 put options. While there is no significant difference in jump risk exposure between the high- and low-DES stocks in Panel A, the relation between jump betas and DES is again nonmonotonic across DES bond portfolios in Panel B. This result is robust even after we take maturity into account.[17]

[15] Herskovic et al. (2016) have documented that idiosyncratic volatility has a common movement that carries a negative price of risk, so the opposite patterns in the volatility exposure of stocks and bonds across DES quintiles can possibly explain a negative DES stock return spread and a positive DES bond return spread.

[16] Bai et al. (2020) show that introducing jumps into a diffusion-based structural model can quantitatively resolve the "credit spread puzzle," so it is possible that DES is a measure of jump exposure because our model abstracts from the jump process and can be misspecified.

[17] Bai et al. (2020) document that short-maturity bonds are more exposed to jump risk than long-maturity

In the second set of tests for the effect of growth options, we include the investment-minus-consumption (IMC) portfolio return (Kogan and Papanikolaou, 2014) and the negative change in the price of equipment relative to nondurable consumption goods (Ishock) as the aggregate investment shock measures in the next two specifications of Table 9. Because of the nature of equity and bond contracts, stocks are expected to capture growth options better than bonds, and we expect that the difference, if any, in their exposure to investment shocks can help explain the cross-sectional stock and bond returns. However, investment shock betas are weak and nonmonotonic across stock and bond DES quintiles. Therefore, we do not find support for the interpretation of growth risk.

In the last attempt to seek a risk-based explanation, we examine the exposure of DES portfolios on the change in interest rates, proxied by the 10-year government bond yield in the last row of each panel in Table 9. If these quintiles have a different duration and exposure to the government bond yield change, they may have different risk premiums. However, we find no evident, monotonic pattern in the exposure to the yield change across these portfolios. For bonds in Panel B, although the long-short portfolio (L-H) has a significant exposure to the change in interest rates, the sign of exposure is negative which goes in the opposite direction to explain the bond DES premium.

Taken together, our extensive attempts in this section do not find empirical support for a risk-based explanation of the stock and bond returns across DES portfolios.

3.5.3 Analyst long-term earnings forecasts

We conclude this section by examining one potential source of local shocks that drive valuation gaps between debt and equity – equity investor overoptimism.

La Porta (1996) documents that companies with high long-term earnings growth forecasts (LTG) earn poor returns relative to companies with low LTG. He interprets this finding as evidence that analysts, as well as investors who follow them or behave like them, are too optimistic about stocks with rapidly growing earnings and too pessimistic about stocks with deteriorating earnings. Here, we examine the relation between DES and equity analyst LTG. If high DES captures equity overpricing relative to debt, one possible contributor of the overpricing could be overly optimistic earnings growth forecasts, which should be gradually corrected in subsequent years.

bonds. In Section B.5 of the Internet Appendix, we double-sort bonds into 3-by-3 portfolios based on their time to maturity and DES. If jump risk is an important driver for the DES premiums, we expect the DES bond return spreads to be stronger among low time-to-maturity bonds. However, the results from the double sorts suggest that the DES premium is in fact larger among long-maturity bonds. Therefore, this combined evidence suggests that jump risk cannot be a major explanation for the DES premium.

We obtain the LTG data from the IBES summary unadjusted file. Table 10 confirms our conjecture. Panel A summarizes the average contemporaneous LTGs across the DES quintiles. The results show a monotonically increasing relation between LTG and DES. Stocks with low DES have a forecasted long-term earnings growth of 10.21% per year, which is significantly smaller than the 12.73% per year seen for stocks with high DES.

[Insert Table 10 here]

In Panel B, we run Fama-MacBeth cross-sectional regressions of cumulative revisions in LTG in the subsequent 12, 24, 36, 48, and 60 months on the DES measure. The estimated coefficient of DES is insignificant in predicting LTG revision in the next 12 months. However, from 24 months up to 60 months, the coefficient of DES is negative and statistically significant, and its magnitude increases monotonically with the forecasting horizon, with the estimated coefficient rising from -0.15 for the 24-month revision to -0.32 for the 60-month revision. These results suggest that the overly optimistic growth forecasts for high DES stocks tend to persist for several years.

Taken together, our findings indicate high DES firms are likely to have overly optimistic earnings growth forecasts that mean-revert subsequently. In the context of the mechanism in Greenwood et al. (2018), the overoptimism-induced demand for stocks can generate a valuation gap between debt and equity. It also results in simultaneous overreaction in stock prices and underreaction in bond prices, hence subsequent stock and bond returns in opposite directions. It is worth emphasizing that market segmentation is needed for our DES measure to capture such overoptimism in the equity markets. If the stock and bond markets are well integrated, the overoptimistic sentiment in the stock market will also be reflected in bond prices, and there will be no valuation gap according to the DES definition.

4 Corporate financing decisions and insider trading

So far we have shown that the implications of the DES measure for asset price dynamics are consistent with theories of market segmentation. In this section, we proceed to validate our measure from the perspective of corporate management. In particular, we are interested in the relation between DES and corporate financing decisions and insider trading. Compared to outside investors, corporate managers might be better at assessing the fair values of the stocks and bonds of their firms. Thus, if DES does reflect the valuation gap between debt and equity, we expect management to take advantage of it by adjusting external financing and insider trading decisions.

4.1 Corporate security issuance

Stein (1996) argues that firms will respond to capital market conditions in their capital budgeting and financing decisions. Baker (2009) further lays out the drivers of supply effects on corporate finance: limited intermediation, investors tastes (non-fundamentally driven shifts in investor preferences or beliefs), and corporate opportunism. A main prediction is that firms will issue securities when their valuations are high and repurchase them when their valuations are low.

It has been well documented that firms time equity markets (see e.g., Ritter, 1991; Baker and Wurgler, 2000; Hong et al., 2008; Dong et al., 2012). However, there is limited evidence of firms' timing debt markets or jointly timing both debt and equity markets. One exception is Ma (2019), who documents that nonfinancial firms arbitrage between the two markets by simultaneously issuing and repurchasing across equity and bond markets. She uses equity valuation ratios and credit spreads (or bond returns) to separately proxy for potential misvaluation of equity and debt. Theoretically, it is the relative mispricing between debt and equity that drives corporate arbitrage behavior; if both equity and debt are mispriced in the same direction, the firm will not necessarily swap one for the other. This is exactly what the DES measure is designed to capture by directly comparing the relative valuations of debt and equity of the same firm.

4.1.1 Panel regressions

To examine the predictive power of DES for corporate financing decisions, we first run panel regressions of quarterly financing activities on lagged DES as follows:

$$Y_{i,t} = a_i + b_t + c\ \mathrm{DES}_{i,t-1} + d\ X_{i,t-1} + e_{i,t}, \tag{14}$$

where $Y_{i,t}$ is net equity issuance, net debt issuance, or change in cash holdings for firm i in quarter t; a_i and b_t are firm and quarterly time fixed effects, and $X_{i,t-1}$ stands for a vector of firm-specific controls. Following Ma (2019), we use actual credit spreads to proxy for debt market misvaluation. We also use the market-to-book equity ratio to proxy for mispricing of equity. In addition, we include standard controls in the literature (see e.g., Leary and Roberts, 2005), including lagged market leverage, log of total assets, profitability, asset tangibility, dividend payout rate, and cash holding (see Table 1 Panel C for the definition of variables).[18] Standard errors are clustered at the firm level.

[18] In Table B7 of the Internet Appendix, we follow Ma (2019) and include profitability and capital investments from the contemporaneous quarter as controls. The main results are unchanged.

[Insert Table 11 here]

Panel A of Table 11 reports the results. Let's first look at net equity issuance. We start with a specification similar to that in Ma (2019) by leaving out the DES measure. The coefficient estimate on lagged market-to-book equity ratio (ME/BE) is positive (consistent with firms with high equity valuation issuing more equity) but statistically insignificant. The coefficient on lagged credit spread (CS^{D}) is marginally significant but negative, likely because firms with high credit spreads can find it difficult to raise external equity. As expected, lagged market leverage is positively and highly significantly related to future equity issuance, consistent with firms raising external equity to reduce leverage ratio. Next, when DES is added to the regression, its coefficient is positive and significant. The positive coefficient implies that firms tend to issue more equity when their equity is more expensive relative to debt. This result is robust whether we control for lagged credit spreads or not.

We next examine net debt issuance. Without including the DES measure, the coefficient estimate for market-to-book equity ratio is negative and significant, consistent with the interpretation that firms with high equity valuation tend to issue less debt. The coefficient on actual credit spreads is positive, again in contradiction with the arbitrage view: firms with low debt valuation appear to issue more debt, not less. This result differs from Ma (2019), who finds credit spreads to be negatively associated with net debt issuance. The discrepancy is likely due to our inclusion of lagged market leverage as a control.[19] Next, the coefficient on DES is negative and significant, implying that firms tend to issue less debt (or retire more debt) when their equity is more expensive relative to debt. Recall that, as shown in Table 2, the DES measure is non-monotonically related to actual credit spreads. The contrast in how DES and actual credit spreads are connected to net equity and debt issuance suggests that the DES measure is likely the more accurate measure of the mispricing of debt relative to equity.

An interesting observation is that the coefficient on DES is larger in magnitude for net debt issuance compared to for net equity issuance, which would imply that the increase in equity issuance associated with higher DES is not sufficient to cover the increase in debt retirement (assuming the ratio of a firm's total external financing to total assets remains stable over time). We find that firms with higher DES also have smaller (or more negative) growth in cash reserves. One possible explanation is that (seasoned) equity issuance requires a longer period of time to plan and complete, and firms might use their cash reserves to retire/buy back undervalued debt in the meantime. In addition, we also find that DES has no significant association with real capital investments or R&D investments (see Section B.8

[19] Without including lagged market leverage, the coefficient for CS^{D} is -0.47 (with a t-statistic of -4.83).

of the Internet Appendix), suggesting that firms primarily respond to the relative mispricing between debt and equity through financial adjustments and not real adjustments.

4.1.2 Logistic regressions

The results above indicate that, in the cross section, DES is positively associated with net equity issuance, negatively associated with net debt issuance, and negatively associated wit changes in cash holdings in the subsequent quarter. The question remains whether the same firms are arbitraging across equity and debt markets to take advantage of the relative mispricing. For example, when equity is overvalued relative to debt, do the same firms simultaneously issue equity and retire their debt?

We answer this question by running logistic regressions to examine the arbitrage behavior of nonfinancial firms as follows:

$$\mathbf{P}(I^k_{i,t} = 1|\text{DES}_{i,t-1}, X_{i,t-1}) = \Phi\left(b_t + c\ \text{DES}_{i,t-1} + d\ X_{i,t-1}\right), \quad k \in \{ED, CD\}. \tag{15}$$

$I^{ED}_{i,t}$ is an indicator variable that equals one if firm i issue equity to retire debt at quarter t, i.e., $I^{ED}_{i,t} = 1_{\{\Delta S_{it}>0, \Delta D_{it}<0\}}$, where ΔS_{it} and ΔD_{it} denote net equity and debt issuance for firm i in quarter t, respectively. This is often referred to as an equity-debt swap. Similarly, $I^{CD}_{i,t}$ equals one if firm i draws down cash reserve to retire debt at quarter t, i.e., $I^{CD}_{i,t} = 1_{\{\Delta C_{it}<0, \Delta D_{it}<0\}}$, where ΔC_{it} denotes the net change in cash holdings. $\Phi(\cdot)$ is the logistic function. We deduct the mean from all the variables to remove firm fixed effect, and include the same set of control variables and quarterly time fixed effect as those in equation (14).

The results are reported in Panel B of Table 11. In the left part of the panel, we look at equity-debt swaps. A higher DES is significantly positively associated with the probability of a firm to issue equity and retire debt in the next quarter. The coefficient on market-to-book equity ratio (ME/BE) is also positive and significant. However, like in panel regressions in Panel A of Table 11, the coefficient on actual credit spreads (CS^{D}) is again negative, in contradiction with the arbitrage view: higher credit spreads are supposed to signal low debt valuation and be associated with more equity-debt swaps. In the right part of the panel, we look at firms' tendency to draw down cash to retire debt. The positive and significant coefficient for DES again confirms that the results in the cross section also holds at firm level: firms with higher DES are more likely to draw down their cash holdings to retire relatively undervalued debt. Again, the coefficient on market-to-book equity ratio is insignificant, while the coefficient on actual credit spreads has the "wrong" sign.

In summary, the unique information content of DES for corporate cross-market arbitrage activities adds further evidence to the hypothesis that DES captures the valuation gap between debt and equity. Our results suggest that a firm could lower its leverage ratio by issuing equity and retiring debt when its equity is relatively overpriced compared to its debt. It is complementary to Baker and Wurgler (2002) and strengthens the findings of Ma (2019). These findings suggest that potential valuation gaps between debt and equity should be an important consideration in studies of corporate financing decisions.

4.2 Insider trading

A company's corporate managers trade their equity-based compensation to maximize their own wealth when they believe the market value deviates from their estimated fair value.[20] In this subsection, we examine how DES is associated with subsequent insider trading. Our conjecture is that firms with high DES engage in more insider stock sales.

We test this conjecture using filing information from Thomas-Reuters Insider Filings from 1986 to 2020. We focus on nonderivative trades from Table 1 of Form 4 and require insiders to hold a role among the top tier of their management team (i.e., with a nonmissing value for the item *rolecode1*). We include observations verified by the data provider (cleanse=R, H, C). Following Cohen et al. (2012), we also remove "routine" trades by insiders.[21]

We obtain the number of shares purchased (acqdisp=A and trancode=P) and sold (acqdis=D and trancode=S) by insiders and construct two measures to proxy for insider selling activities each quarter, including the fraction of insider sales volume (the number of shares sold divided by the total number of shares traded each month) and the fraction of insider sales (the number of sales divided by the total number of trades each month). We then merge monthly insider trading measures with our DES measure as well as quarterly Compustat data.

To examine insider trading, we run panel regression as follows:

$$Y_{i,t} = a_i + b_t + c \ \mathrm{DES}_{i,t-1} + d \ X_{i,t-1} + e_{i,t}, \tag{16}$$

where the dependent variable $Y_{i,t}$ is the fraction of insider sales volume and the fraction of insider sales, $X_{i,t-1}$ stands for a vector of firm-specific control variables, and $e_{i,t}$ is the error term for firm i at quarter t. We follow Guay et al. (2021) and include the logarithm of total

[20]Evidence of informed insider trades can be traced back to Jaffe (1974). A nonexclusive list of works in this large literature includes Lee (1997), Lakonishok and Lee (2001), and Cohen et al. (2012) among many others.

[21]Each year, we identify routine traders who have traded in the same calendar month in the previous three years.

assets, profitability, book leverage, and market-to-book equity ratio (ME/BE) as control variables. We also include firm and time fixed effects and cluster standard errors at the firm level.

[Insert Table 12 here]

Table 12 reports the results. When the dependent variable is the fraction of insider sales volume, the coefficients of DES range from 1.56 to 2.14, which implies increased selling among insiders of high-DES firms. Second, the coefficient of DES remains statistically significant when we include the mispricing score in a shorter sample that ends in 2016. Third, interestingly, while the ME/BE ratio suggests more insider selling, the negative estimate of MispScore effectively implies fewer sales made by insiders. The latter result may be surprising but can be a result of the correlations of MispScore with other control variables such as the ME/BE ratio.

In conclusion, the results in this section provide additional validation for DES as a measure of the relative mispricing between debt and equity markets from the perspective of corporate decisions.[22]

5 Conclusion

Since market segmentation is a necessary condition for valuation gaps between debt and equity to exist and persist, one can infer the degree of market segmentation based on how pronounced the valuation gaps are. We construct a measure of the valuation gap between debt and equity of the same firm, the debt-equity spread (DES), as the difference between actual credit spreads and the equity-implied credit spreads. We validate that DES indeed reflects relative mispricing between debt and equity by examining its connections with future stock and bond returns, corporate financing decisions, and insider trading patterns.

We have the following main findings. First, consistent with theory predictions, DES negatively predicts the cross section of stock returns while positively predicting the bond returns. The predictive power of DES for both stock and bond returns is increasing in a variety of proxies for limits to arbitrage. We also rule out several potential risk-based explanations for the return predictability, such as shocks to systematic volatility or common component of idiosyncratic volatility, jump risks, and investment-specific technology shocks. Second, firms

[22]Our results are nearly identical when we change the dependent variable to the fraction of insider sales. Moreover, in Section B.9 of the Internet Appendix, we use an alternative sample that includes routine trades and perform additional tests. The results in Table B9 are very similar to those in Table 12. Therefore, our results are not driven by the exclusion of "routine" trades.

with higher DES have higher long-term earnings growth forecasts by equity analysts that tend to be revised downward in subsequent years, suggesting that overly optimistic forecasts by equity investors could be a source of the valuation gaps captured by DES. Third, we find evidence that firms with higher DES try to arbitrage the relative mispricing by simultaneously issuing equity and retiring debt. Fourth, the insiders of high DES firms are more likely to sell their stocks.

The collective evidence indicates that our valuation gap measure, DES, likely contains important information about the relative mispricing between debt and equity. It implies that that segmentation between the two markets is prevalent at firm level. It also suggests that such valuation gaps should be an important consideration in our studies of asset price dynamics and corporate financing decisions.

Extending the structural model to take into account jump risks (see, e.g., Bai et al., 2020), secondary market liquidity (see e.g., Chen et al., 2018), and more detailed information about the capital structure (such as debt seniority, callability, or maturity structure, as in Chen et al., 2021) could further improve the quality of the valuation gap measure. We leave these considerations for future research.

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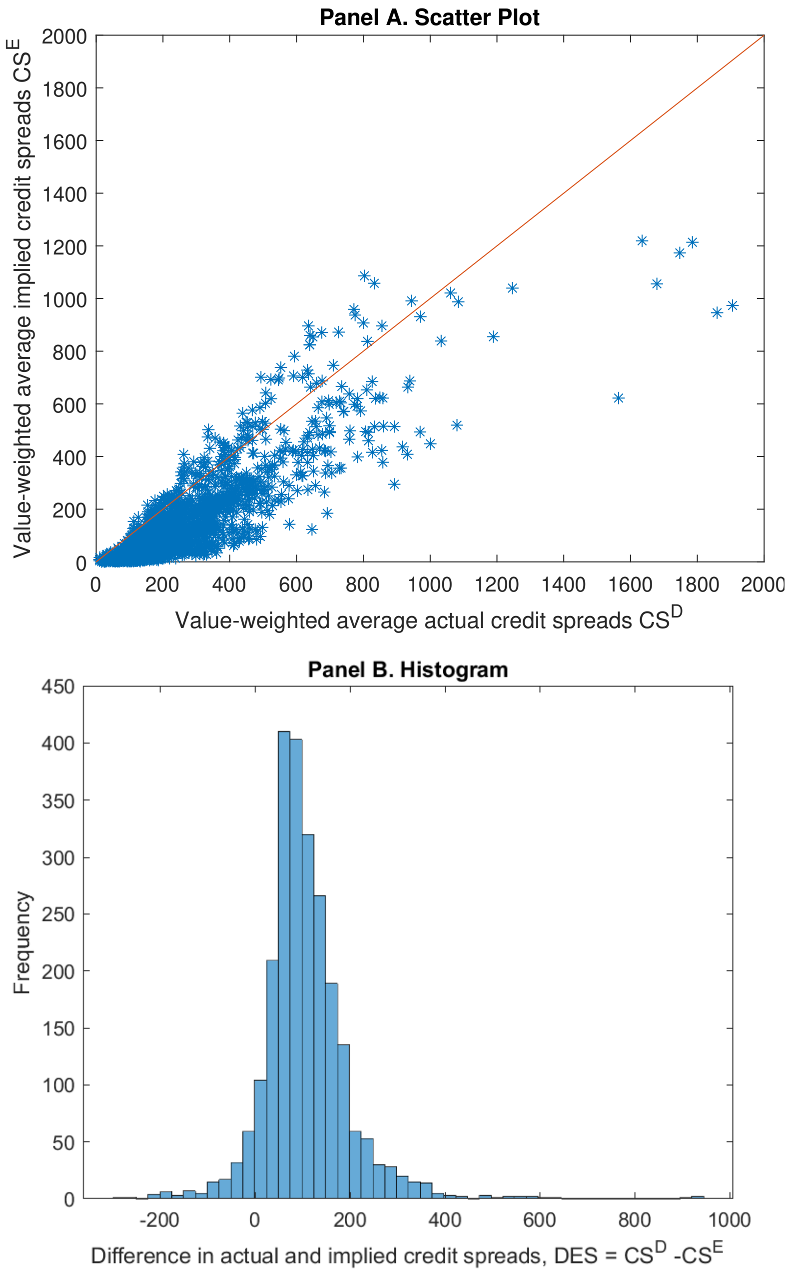


Figure 1: **Performance of the extended CreditGrades model**
Panel A plots the model-implied credit spreads against actual credit spreads across five quintile portfolios sorted by actual credit spreads. Firm-level credit spreads (for both actual and implied) are computed as the bond market value-weighted average credit spreads across all bonds within a firm. Portfolio-level credit spreads (for both actual and implied) are computed as the equity market value-weighted average credit spreads across all firms within a portfolio. Panel B plots the histogram of portfolio-level DES. The sample ranges from January 1980 to December 2020.

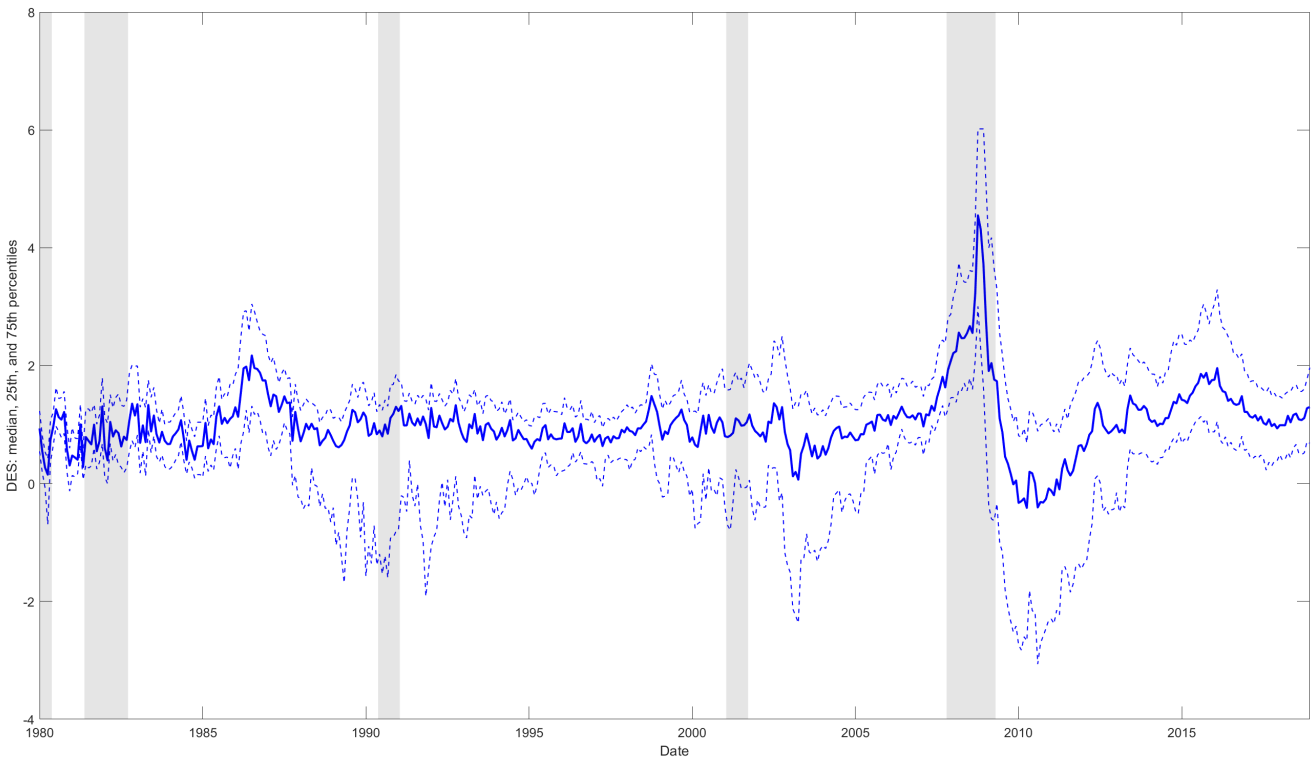
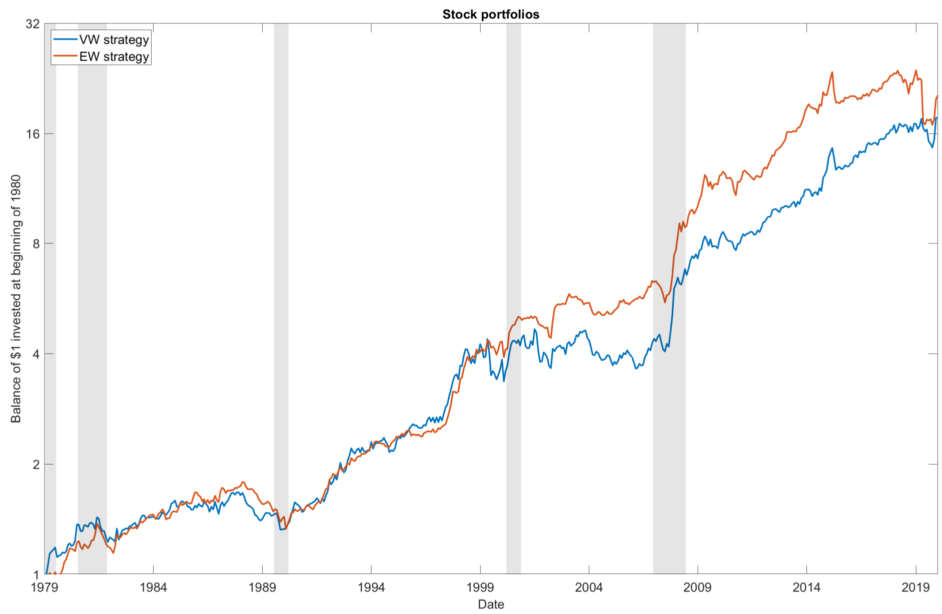


Figure 2: **Times series of DES distribution**
This figure plots the time series of the median, 25th percentile, and 75th percentile of portfolio-level DES. The gray bars represent NBER recessions. The sample ranges from January 1980 to December 2020.



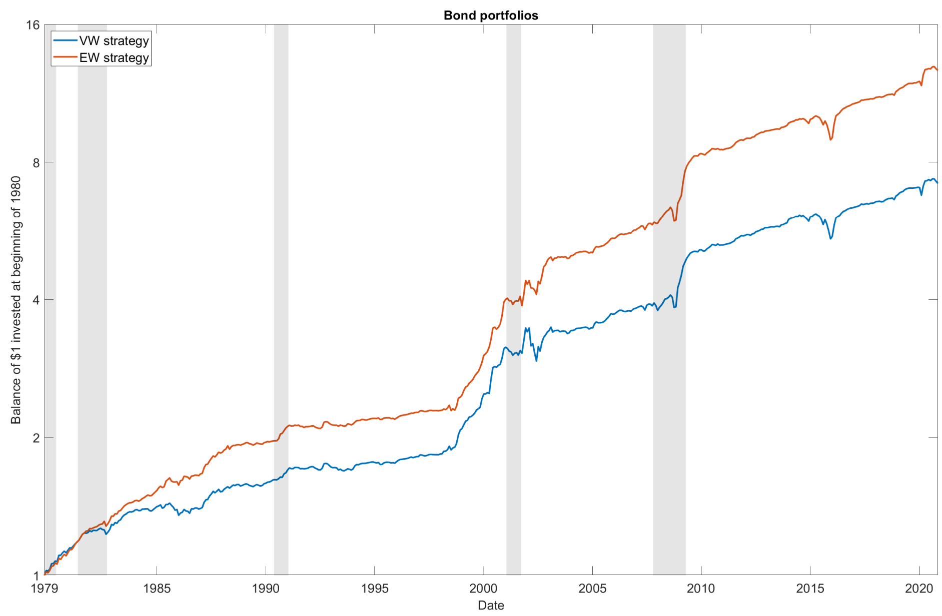


Figure 3: **Cumulative returns of DES long-short portfolios**
This figure plots the time series of the balance of $1 invested in the long-short DES portfolio at the beginning of 1980 for both the value-weighted (VW) scheme and the equally weighted (EW) scheme. The top panel is for the stock portfolios, and the bottom panel is for the bond portfolios. The gray bars represent NBER recessions.

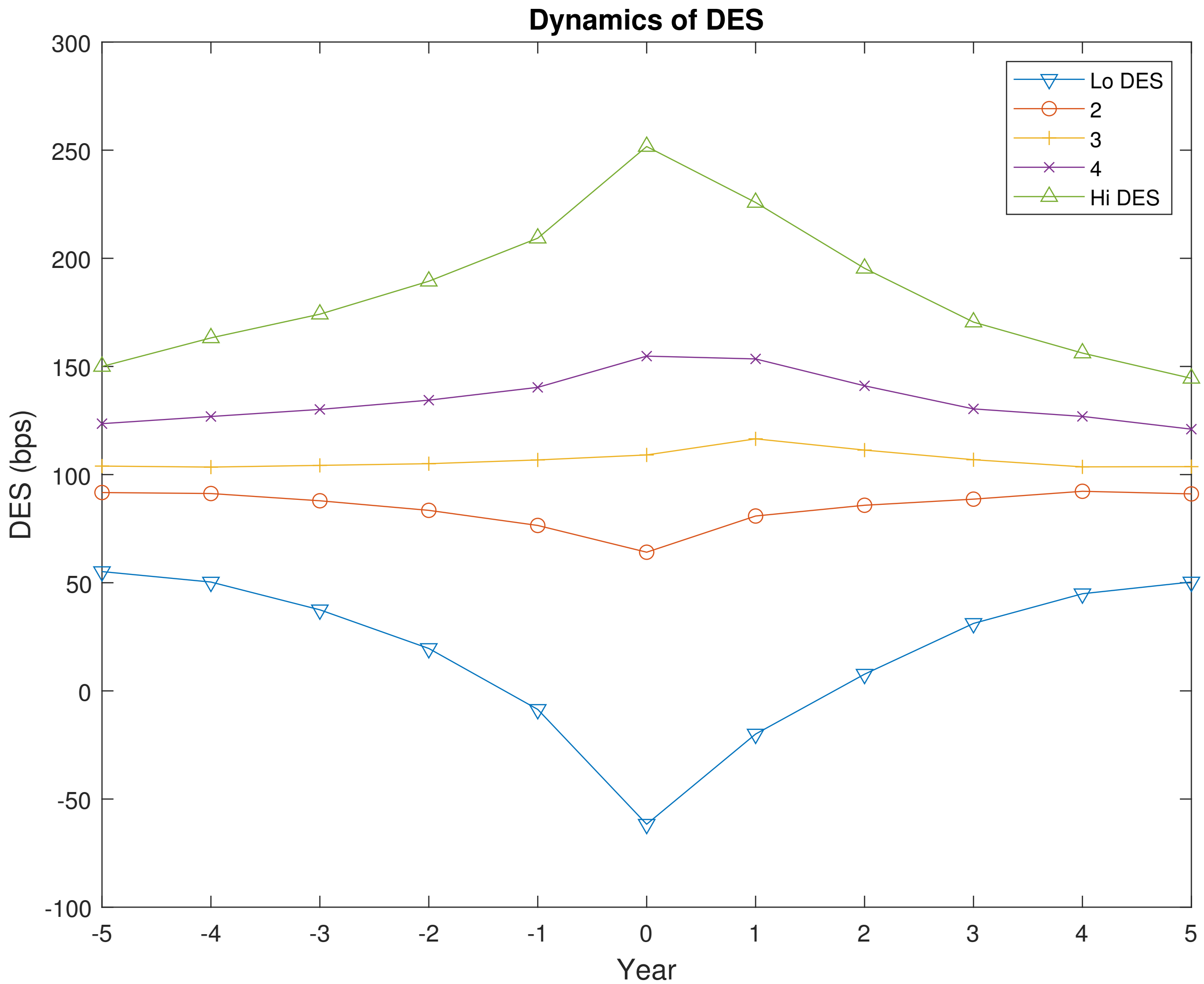


Figure 4: **Dynamics of DES around portfolio formation**
This figure plots the dynamics of average DES (in bps) five years before and five years after DES quintile portfolio formations. The sample is from January 1980 to December 2020.

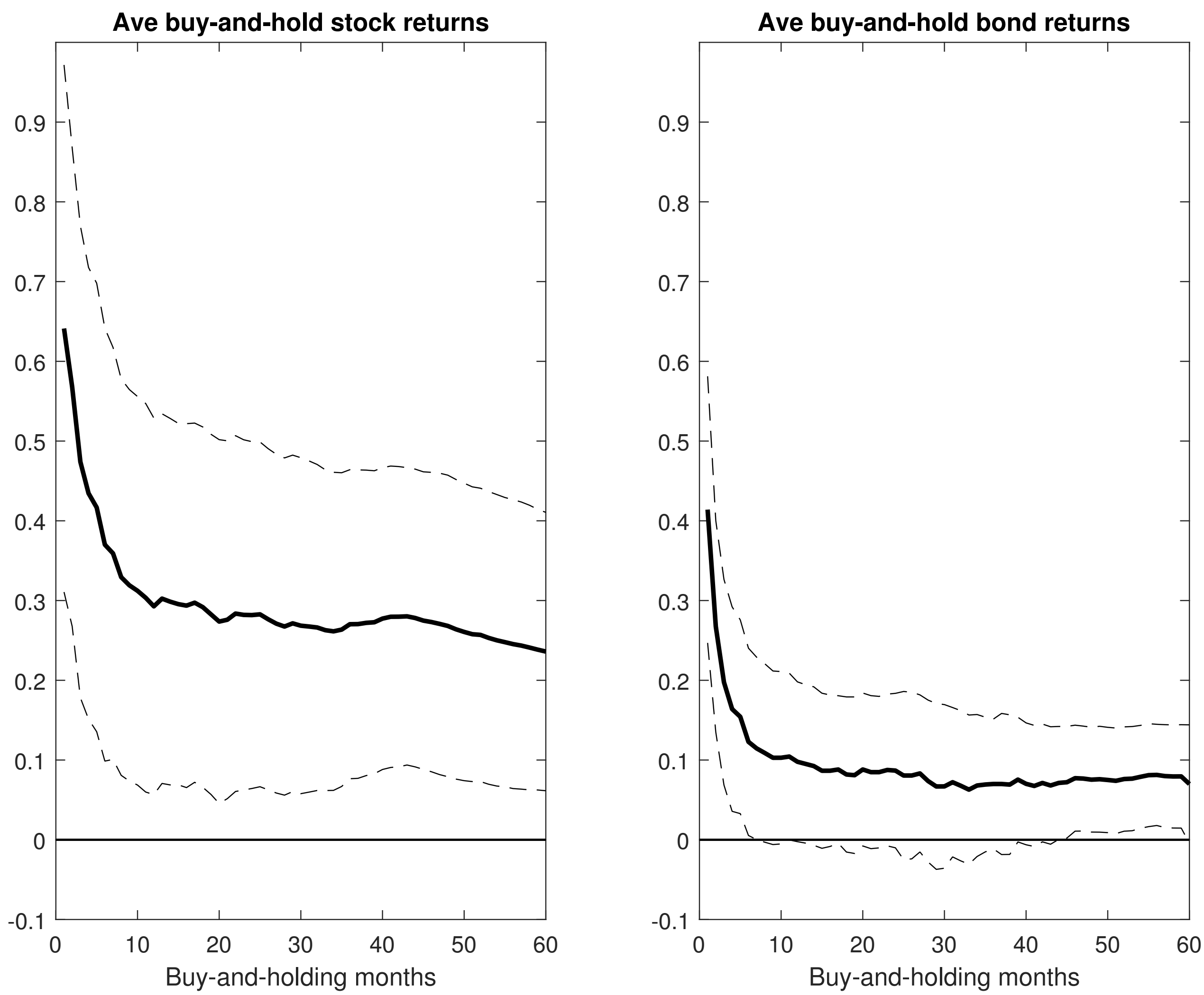


Figure 5: **Long-term return prediction of debt-equity spread (DES)**
This figure plots the average monthly buy-and-hold return of the long-short DES stock (left panel) and bond (right panel) portfolio for a holding period ranging from 1 to 60 months. The point estimate (solid line) and 95% confidence interval (dashed lines) are plotted for each horizon. Newey-West standard errors with lag = K+2 control for heteroskedasticity and autocorrelation, where K is the predictive horizon. The sample is from January 1980 to December 2020.

Table 1: **Variable Definitions**
This table contains the definitions and descriptions of the variables used in the paper.

Panel A. Firm characteristics	
Idiosyncratic volatility (Ivol)	Standard deviation of the regression residuals of daily stock excess returns on the Fama and French (1992) factor model (Source: CRSP)
Financial leverage (MLev)	Ratio of total debt (sum of Compustat items DLC and DLTT) to asset market value (sum of Compustat items DLC and DLTT and market cap at the December of the same year) (Source CRSP and Compustat)
Failure probability (FP)	Probability of a firm going bankrupt or delisted, based on Campbell et al. (2008) (Source: CRSP and Compustat)
Momentum (Mom)	Prior 2- to 12-month cumulative returns (Source: CRSP)
Asset growth (AG)	Growth rate of total assets (Compustat item AT) from the previous year (Source: Compustat)
Mispricing score (MispScore)	Firm-level mispricing measure from Stambaugh et al. (2012)
Monthly dollar volume (Dvol)	Month-end price times trading volume in that month (Source: CRSP)
Days to cover (DOC)	Number of shares sold short in the month divided by average trading volume (Source: SEC)
Equity lending fee (SAF)	12-month moving average of simple average fee (Source: Markit)
Analyst forecast dispersion (FDisp)	Standard deviation of forecasted earnings per share in June of each year divided by stock price at the end of June (Source: IBES)

Panel B. Bond characteristics	
Bond size (BondSize)	Bond price times the amount outstanding (Source: TRACE)
Amihud's liquidity	Median value of absolute changes in daily bond prices divided by trade volume each month (Source: TRACE)
Monthly dollar volume (Dvol)	Month-end price times trading volume in that month (Source: TRACE)
Gamma	Negative of price autocorrelation (Bao et al., 2011) (Source: TRACE)
Number of trading days	Number of days that a bond is traded in a month (Source: TRACE)

Panel C. Corporate activities and insider trading	
Net equity issuances	Equity issuance (Compustat item SSTKQ) minus equity repurchase (PRSTKCQ), divided by total assets (ATQ) of the previous quarter (Source: Compustat)
Net debt issuances	Short-term debt change (Compustat item DLCCQ) plus long-term debt net issuance (DLTISQ - DLTRQ), divided by total assets (Compustat item ATQ) of the previous quarter (Source: Compustat)
Fraction of insider sales volume	Ratio of shares sold to total number of shares traded by insiders each month (Source: Thomas-Reuters Insider Filings)
Fraction of insider sales	Ratio of sales divided by the total number of trades each month
Log total assets (Log(BA))	Logarithm of total assets (item AT) (Source: Compustat)
Profitability	Operating income divided by total assets of last period (OIBDP/AT) (Source: Compustat)
Tangibility	Property, plants, and equipment divided by total assets (PPENT/AT) (Source: Compustat)
Dividend	Quarterly cash dividend converted from (DVY), divided by total assets (Compustat item ATQ) of the previous quarter (Source: Compustat)
Cash holding	Cash and short-term investments (CHE), divided by total assets (AT) of the previous year (Source: Compustat)
Market-to-book equity (ME/BE)	Ratio of market value of equity to book value (Source: Compustat)
Market leverage (MLev)	Total debt divided by the sum of debt and equity ((DLC + DLTT)/(PRCC×CSHO + DLC + DLTT))

Table 2: **Summary statistics of debt-equity spread quintile portfolios**
This table reports summary statistics of the characteristics of quintile portfolios sorted by the debt-equity spread (DES). Panel A reports the average number of stocks, average DES and the inputs in computing it, including CS^E, CS^D, asset volatility (Avol), leverage ratio (Lev), payout rate (Payout), and bond maturity and duration for each of the DES quintiles. Panel B reports other firm characteristics, including idiosyncratic volatility (Ivol), market leverage ratio (Mlev), failure probability (FP), firm size (Size, in billion dollars), book-to-market equity ratio (BM), momentum (Mom), gross profitability (GP), asset growth (AG), Amihud illiquidity (Illiq), dollar volume (Dvol, in billion dollars), days to cover (DTC), equity lending fee, measured by simple average fee from Markit (SAF), analyst forecast dispersion (FDisp), and mispricing score (MispScore) from Stambaugh et al. (2012). A portfolio's average value of each characteristic is computed as the time series mean of the cross-sectional median for that portfolio. The sample is monthly from January 1980 to December 2020.

Panel A. DES and its inputs

	L(ow)	2	3	4	H(igh)
N	66.67	67.23	67.24	67.23	66.85
DES	−61.64	64.12	109.09	154.77	251.69
CS^E	318.71	71.67	34.14	29.76	52.76
CS^D	225.67	135.23	145.76	191.04	330.93
Avol	0.17	0.18	0.19	0.19	0.20
Lev	0.50	0.30	0.27	0.28	0.32
Payout	0.06	0.04	0.04	0.04	0.04
Maturity	9.06	11.10	11.28	10.71	9.30
Duration	5.56	6.47	6.41	6.09	5.28

Panel B. Firm characteristics

	L(ow)	2	3	4	H(igh)
Ivol	1.684	1.340	1.313	1.396	1.613
Mlev	0.476	0.271	0.251	0.268	0.333
FP	−7.599	−8.043	−8.102	−8.066	−7.915
Size	3.573	9.117	7.405	4.430	2.063
BM	0.755	0.595	0.561	0.581	0.653
Mom	0.051	0.098	0.115	0.118	0.104
GP	0.212	0.273	0.293	0.287	0.258
AG	0.046	0.065	0.065	0.062	0.060
Illiq	0.002	0.001	0.001	0.002	0.004
Dvol	6.549	12.996	11.037	7.090	3.208
DTC	4.088	3.320	3.446	3.937	5.000
SAF	29.057	28.318	28.168	28.389	29.704
FDisp	0.004	0.002	0.002	0.002	0.003
MispScore	49.361	44.972	44.068	45.426	48.720

Table 3: **Average returns and alphas**

This table reports average annualized excess returns and abnormal returns for stocks and bonds. In Panel A, we form stock quintile portfolios based on the firm-level debt-equity spread (DES) of the previous month and then estimate the stock alphas from CAPM, Fama and French (1992) three-factor model (FF3), Carhart four-factor model (C4), Fama and French (2015) five-factor model (FF5), Stambaugh and Yuan (2017) mispricing factor model (M4), and Hou et al. (2015) q-factor model (HXZ). In Panel B, we form the bond quintile portfolios based on the bond-level DES of the previous month and then estimate the one-factor bond alphas, α^{mkt}, by regressing excess bond returns on an intercept and the market bond returns (proxied by the Merrill Lynch Index) and estimate the four-factor bond alpha α^{4F}, by regressing the excess bond returns on an intercept and four bond factors proposed by Bai et al. (2019). The sample is monthly from January 1980 to December 2020, except for the bond four-factor model tests, where the sample period is from July 2004 to December 2019 because of the availability of the Bai et al. (2019) factors. We report the results using both the value-weighted (VW) scheme and the equal-weighted (EW) scheme. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12.

Panel A: Stock returns

VW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	12.29	9.50	6.76	7.39	4.57	7.72
	(4.56)	(4.42)	(3.05)	(2.76)	(1.55)	(4.29)
α^{CAPM}	3.75	1.99	−0.79	−0.39	−4.36	8.10
	(2.60)	(2.04)	(−0.83)	(−0.36)	(−2.80)	(4.13)
α^{FF3}	2.55	1.73	−0.81	−0.77	−5.12	7.67
	(1.87)	(1.80)	(−0.86)	(−0.73)	(−3.62)	(3.59)
α^{C4}	4.06	2.19	−0.70	−0.91	−4.22	8.28
	(3.38)	(1.97)	(−0.70)	(−0.85)	(−2.73)	(3.83)
α^{FF5}	1.70	0.54	−2.74	−2.83	−5.51	7.20
	(1.20)	(0.50)	(−3.33)	(−2.46)	(−3.59)	(3.11)
α^{M4}	3.22	1.49	−1.84	−1.70	−3.87	7.09
	(1.80)	(1.24)	(−1.79)	(−1.14)	(−2.09)	(2.45)
α^{HXZ}	2.58	0.59	−1.32	−1.79	−3.46	6.04
	(1.57)	(0.47)	(−1.27)	(−1.23)	(−1.68)	(2.11)
EW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	14.99	11.57	8.55	9.08	7.06	7.93
	(4.67)	(5.05)	(3.69)	(3.49)	(2.27)	(4.33)
α^{CAPM}	4.91	3.19	0.55	0.39	−3.24	8.15
	(2.26)	(2.29)	(0.40)	(0.31)	(−1.60)	(4.19)
α^{FF3}	3.08	2.10	−0.21	−0.63	−4.77	7.85
	(1.89)	(1.85)	(−0.19)	(−0.66)	(−2.97)	(3.66)
α^{C4}	5.83	3.31	0.48	0.08	−2.40	8.23
	(3.92)	(3.09)	(0.52)	(0.10)	(−1.60)	(3.72)
α^{FF5}	2.00	0.41	−2.44	−2.83	−5.22	7.21
	(1.26)	(0.37)	(−2.67)	(−3.01)	(−3.07)	(3.59)
α^{M4}	6.33	2.18	−0.86	−1.35	−1.93	8.26
	(2.96)	(1.68)	(−0.80)	(−0.97)	(−1.09)	(3.21)
α^{HXZ}	4.85	1.28	−1.34	−1.49	−2.07	6.92
	(2.27)	(0.82)	(−0.95)	(−1.04)	(−0.85)	(2.58)

Panel B: Bond returns

VW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.42	3.36	4.23	4.84	7.39	−4.97
	(1.78)	(2.57)	(3.47)	(4.01)	(5.74)	(−5.41)
α^{mkt}	−1.75	−1.04	−0.09	0.72	3.39	−5.13
	(−3.12)	(−2.17)	(−0.21)	(1.74)	(4.96)	(−5.86)
α^{4f}	−1.03	0.04	0.87	0.92	1.83	−2.86
	(−1.66)	(0.08)	(1.43)	(1.66)	(1.82)	(−2.05)

EW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.30	3.10	4.20	5.04	8.65	−6.35
	(1.73)	(2.31)	(3.47)	(4.26)	(6.03)	(−6.37)
α^{mkt}	−1.71	−1.15	−0.05	0.93	4.63	−6.35
	(−3.05)	(−2.24)	(−0.15)	(2.63)	(6.19)	(−6.70)
α^{4f}	−0.89	−0.12	0.60	1.16	2.15	−3.04
	(−1.36)	(−0.24)	(1.18)	(2.01)	(2.34)	(−2.31)

Table 4: **Fama-MacBeth regressions**

This table reports the results from monthly Fama-MacBeth return predictive regressions. In Panel A, we run cross-sectional regressions of stock returns on the firm-level debt-equity spread (DES) and firm characteristics, such as idiosyncratic volatility (Ivol), market leverage ratio (Mlev), failure probability (FP), firm size (Size, in billion dollars), book-to-market equity ratio (BM), momentum (Mom), gross profitability (GP), asset growth (AG), tangibility, Stambaugh, Yu, and Yuan (2012) mispricing score (MispScore), and lagged one-month bond returns (Lagged-1m BondRet). In Panel B, we run bond returns on the bond-level DES, firm characteristics and bond characteristics, such as logarithm of bond size (LogBondSize), age, amount outstanding (Amount), coupon payment, lagged one-month stock returns (Lagged-1m StockRet). The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is monthly from January 1980 to December 2020, except for Specifications 7 and 8, which end on December 2016 because of the data availability of MispScore.

Panel A: Stock returns									
	1	2	3	4	5	6	7	8	9
Intercept	1.34	−0.24	1.33	1.23	1.00	0.31	2.36	1.47	0.02
	(6.49)	(−0.20)	(2.67)	(4.25)	(1.79)	(0.29)	(8.75)	(1.32)	(0.01)
DES	−0.16	−0.17	−0.16	−0.18	−0.18	−0.19	−0.20	−0.23	−0.20
	(−4.45)	(−5.65)	(−5.01)	(−4.88)	(−5.38)	(−6.66)	(−5.33)	(−6.44)	(−6.72)
Ivol		−0.07				−0.11		−0.13	−0.12
		(−0.91)				(−1.54)		(−1.66)	(−1.68)
Mlev		0.37				−0.05		0.10	−0.02
		(1.13)				(−0.14)		(0.26)	(−0.04)
FP		−0.18				−0.16		−0.18	−0.18
		(−1.33)				(−1.21)		(−1.34)	(−1.32)
logSize			−0.05		−0.05	−0.09		−0.14	−0.08
			(−1.06)		(−1.18)	(−2.11)		(−3.54)	(−1.91)
BM			0.15		0.31	0.31		0.26	0.31
			(1.27)		(2.42)	(2.26)		(1.96)	(2.34)
Mom			0.35		0.24	0.27		0.14	0.29
			(0.95)		(0.67)	(0.84)		(0.42)	(0.89)
GP				0.52	0.98	0.83		0.58	0.85
				(2.01)	(3.15)	(2.65)		(1.99)	(2.72)
AG				−0.55	−0.39	−0.48		0.05	−0.46
				(−2.83)	(−2.50)	(−3.53)		(0.21)	(−3.53)
Tangibility				0.07	0.02	−0.03		0.13	−0.01
				(0.29)	(0.11)	(−0.12)		(0.60)	(−0.04)
MispScore							−0.02	−0.02	
							(−3.94)	(−2.80)	
Lagged-1m BondRet									0.01
									(0.98)
Adj. R^2	1.50	7.44	8.09	5.13	11.08	14.60	3.01	15.08	15.05

Panel B: Bond returns									
	1	2	3	4	5	6	7	8	9
Intercept	0.28	0.48	0.13	0.40	−0.56	−1.24	0.34	0.36	−1.36
	(2.62)	(1.65)	(0.61)	(1.15)	(−1.34)	(−2.55)	(2.52)	(0.87)	(−2.84)
DES	0.13	0.16	0.16	0.18	0.12	0.13	0.14	0.19	0.13
	(5.20)	(5.93)	(5.64)	(5.86)	(5.13)	(5.29)	(5.29)	(5.49)	(5.25)
Ivol		−0.03		−0.01		−0.07		−0.03	−0.07
		(−0.80)		(−0.36)		(−2.03)		(−0.78)	(−2.04)
Mlev		0.42		0.51		0.28		0.44	0.25
		(4.76)		(3.76)		(2.74)		(3.07)	(2.61)
FP		0.04		0.10		−0.03		0.09	−0.04
		(1.04)		(2.16)		(−0.95)		(1.85)	(−1.18)
logSize			0.01	0.05		0.06		0.05	0.07
			(0.50)	(2.78)		(3.37)		(2.60)	(3.60)
BM			0.11	0.05		−0.03		0.08	−0.03
			(2.26)	(1.23)		(−0.78)		(1.74)	(−0.71)
Mom			0.13	0.20		0.29		0.26	0.32
			(1.39)	(3.72)		(4.48)		(4.66)	(4.54)
GP			−0.07	0.08		0.07		0.09	0.03
			(−0.87)	(1.30)		(1.18)		(1.23)	(0.64)
AG			−0.14	−0.13		−0.04		−0.15	−0.03
			(−2.92)	(−2.83)		(−1.09)		(−2.80)	(−0.84)
Tangibility			−0.09	−0.12		−0.08		−0.12	−0.10
			(−1.86)	(−2.68)		(−1.81)		(−2.33)	(−2.29)
MispScore							−0.00	−0.00	
							(−0.98)	(−0.18)	
logBondSize					−2.37	−3.30			−3.42
					(−3.89)	(−4.42)			(−4.51)
Amount					2.40	3.29			3.41
					(3.88)	(4.44)			(4.52)
Age					0.00	−0.00			−0.00
					(0.36)	(−0.16)			(−0.42)
Coupon					0.05	0.10			0.11
					(1.93)	(3.46)			(3.74)
Maturity					0.01	0.00			0.00
					(1.46)	(0.42)			(0.32)
Lagged-1m StockRet									1.45
									(5.23)
Adj. R^2	2.43	9.53	9.45	13.56	13.56	26.85	4.06	13.83	27.59

Table 5: **Fama-MacBeth regressions on extended CreditGrades model inputs**
This table reports the results from monthly Fama-MacBeth return predictive regressions with the inclusion of the extended CreditGrades model inputs. In Panel A, we run cross-sectional regressions of stock returns on the firm-level debt-equity spread (DES) and CreditGrades model input variables, such as asset volatility (Avol), leverage ratio (Lev), payout ratio (Payout), equity-implied credit spread CS^E, and actual credit spread CS^D. In Panel B, we run bond returns on the bond-level DES, the above-mentioned firm characteristics, and bond maturity, an indicator for callable bonds, and bond-level equity-implied credit spread CS^E and actual credit spread CS^D. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is monthly from January 1980 to December 2020.

Panel A. Stock returns									
	1	2	3	4	5	6	7	8	9
Intercept	1.34	1.80	0.84	0.90	1.65	0.98	1.27	1.18	1.27
	(6.49)	(6.21)	(4.54)	(3.98)	(3.68)	(5.44)	(7.93)	(7.45)	(7.90)
DES	−0.16				−0.15		−0.20		−0.18
	(−4.45)				(−4.29)		(−3.75)		(−3.95)
AVol		−3.37			−2.77				
		(−2.78)			(−1.76)				
Lev			0.78		−0.08				
			(1.55)		(−0.10)				
Payout				5.74	1.37				
				(3.30)	(0.70)				
CS^E						0.08	−0.02		
						(1.53)	(−0.30)		
CS^D								−0.05	−0.02
								(−0.90)	(−0.25)
Adj. R^2	1.50	2.26	2.33	0.70	7.08	3.32	4.98	3.72	4.94

Panel B. Bond returns											
	1	2	3	4	5	6	7	8	9	10	11
Intercept	0.28	0.27	0.38	0.32	0.30	0.36	−0.27	0.38	0.07	0.11	0.07
	(2.62)	(2.31)	(3.62)	(3.07)	(4.06)	(3.51)	(−1.36)	(3.88)	(0.60)	(0.97)	(0.62)
DES	0.13						0.15		0.23		0.12
	(5.20)						(5.81)		(6.28)		(5.52)
AVol		0.64					0.80				
		(2.37)					(1.85)				
Lev			−0.01				0.56				
			(−0.05)				(1.75)				
Payout				1.35			2.43				
				(2.86)			(4.07)				
Maturity					0.01		0.01				
					(2.80)		(2.09)				
Call						0.03	−0.05				
						(1.26)	(−1.98)				
CS^E								−0.00	0.11		
								(−0.12)	(3.32)		
CS^D										0.14	0.11
										(4.31)	(3.27)
Adj. R^2	2.43	1.07	3.11	0.78	8.71	0.79	18.18	4.34	10.55	9.19	10.55

Table 6: **The role of limits to arbitrage: Stock portfolios**
This table reports the average annualized value-weighted excess returns and Carhart four-factor model abnormal returns of the debt-equity spread (DES) portfolios, conditional on different levels of limits to arbitrage. Each month we sequentially sort firms into 3-by-3 portfolios based on proxies of limits to arbitrage and DES. The measures of limits to arbitrage include firm size, Amihud illiquidity (Amihud, 2002), dollar volume, days to cover, equity lending fee, and analyst forecast dispersion. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is monthly from January 1980 to December 2020 for firm size, illiquidity, and dollar volume, from May 1998 to February 2018 for days to cover, and from January 2008 to December 2020 for equity lending fee.

Panel A. Size

	Excess returns				Carhart 4-factor alphas			
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	15.03	9.54	7.78	7.25	3.83	−1.39	−3.42	7.24
	(4.71)	(3.46)	(2.36)	(3.94)	(2.48)	(−1.39)	(−2.07)	(3.03)
Mid	11.95	8.97	7.70	4.25	2.75	0.21	−2.13	4.88
	(4.71)	(3.88)	(2.94)	(3.54)	(2.32)	(0.18)	(−1.83)	(3.68)
Hi	10.57	7.15	6.84	3.74	3.45	−0.18	−0.34	3.79
	(4.42)	(3.40)	(2.60)	(2.55)	(3.00)	(−0.17)	(−0.36)	(2.44)

Panel B. Illiquidity

	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	10.27	7.37	6.25	4.02	2.88	−0.03	−1.41	4.29
	(4.07)	(3.62)	(2.49)	(2.88)	(2.53)	(−0.03)	(−1.52)	(2.67)
Mid	12.27	9.45	7.29	4.98	3.69	1.51	−1.68	5.37
	(4.84)	(3.98)	(2.61)	(2.91)	(2.91)	(1.17)	(−1.59)	(3.41)
Hi	14.77	9.11	7.43	7.33	5.72	−0.33	−2.50	8.21
	(4.33)	(3.33)	(2.37)	(3.39)	(3.06)	(−0.29)	(−1.63)	(3.09)

Panel C. Dollar volume

	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	16.18	9.17	7.37	8.81	6.74	0.37	−2.01	8.75
	(5.39)	(3.68)	(2.56)	(4.94)	(3.78)	(0.28)	(−1.35)	(3.64)
Mid	11.81	9.17	8.56	3.25	4.10	1.47	−0.40	4.50
	(5.06)	(4.07)	(3.31)	(2.34)	(3.54)	(1.24)	(−0.44)	(3.45)
Hi	10.19	7.33	6.03	4.16	2.61	−0.18	−1.67	4.28
	(4.06)	(3.48)	(2.30)	(2.80)	(2.41)	(−0.17)	(−1.62)	(2.60)

Panel D. Days to cover								
	Excess returns				Carhart 4-factor alphas			
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	9.22	5.64	6.71	2.52	3.96	1.26	2.46	1.50
	(2.20)	(1.68)	(1.77)	(0.83)	(2.29)	(0.84)	(1.28)	(0.54)
Mid	9.62	4.32	2.75	6.87	4.39	−0.19	−2.43	6.82
	(2.66)	(1.36)	(0.71)	(3.10)	(2.58)	(−0.18)	(−1.30)	(2.60)
Hi	10.66	2.72	2.25	8.41	4.38	−3.23	−4.44	8.82
	(2.21)	(0.65)	(0.41)	(2.04)	(1.64)	(−1.66)	(−1.59)	(1.84)

Panel E. Equity lending fee								
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	13.72	10.21	10.81	2.91	3.16	0.32	0.39	2.77
	(3.29)	(2.45)	(2.27)	(1.57)	(2.19)	(0.20)	(0.21)	(1.24)
Mid	15.32	7.35	6.32	9.00	6.66	−2.02	−4.47	11.13
	(3.90)	(1.89)	(1.27)	(3.20)	(3.58)	(−1.36)	(−2.44)	(3.60)
Hi	17.14	8.50	3.92	13.22	6.86	−0.98	−7.24	14.10
	(3.27)	(1.97)	(0.64)	(3.61)	(2.11)	(−0.70)	(−2.85)	(2.97)

Panel F. Forecast dispersion								
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	11.70	8.38	9.38	2.32	5.16	1.52	0.99	4.17
	(5.24)	(3.84)	(3.52)	(1.48)	(3.25)	(1.99)	(0.60)	(2.05)
Mid	11.05	5.29	6.03	5.01	3.04	−2.52	−1.86	4.90
	(3.81)	(2.08)	(2.27)	(2.94)	(2.09)	(−2.20)	(−1.69)	(2.69)
Hi	11.07	4.35	4.57	6.50	2.31	−4.43	−4.92	7.23
	(3.62)	(1.39)	(1.32)	(2.52)	(1.16)	(−2.32)	(−2.60)	(2.56)

Table 7: **The role of limits to arbitrage: Bond portfolios**

This table reports the average annualized value-weighted excess returns and Bai et al. (2019) four-factor model abnormal returns of the debt-equity spread (DES) portfolios, conditional on levels of limits to arbitrage. Each month we sequentially sort bonds into 3-by-3 portfolios based on proxies of limits to arbitrage and DES. The measures of limits to arbitrage include bond size, Amihud illiquidity, dollar volume, gamma (Bao et al., 2011), and number of trading days each month. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is monthly from January 1980 to December 2020 for bond size, Amihud illiquidity, and dollar volume, and from August 2002 to December 2020 for Amihud illiquidity and bond gamma. All four-factor model tests are performed between July 2004 and June 2019 because of data availability.

Panel A. Bond size

	Excess returns				4-factor alphas			
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	1.96	4.59	8.99	−7.03	−0.52	0.74	2.38	−2.90
	(1.36)	(3.76)	(5.78)	(−5.63)	(−0.90)	(1.65)	(2.63)	(−2.40)
Mid	2.71	4.00	6.35	−3.64	−0.50	0.74	1.69	−2.20
	(2.04)	(3.30)	(5.62)	(−5.94)	(−1.37)	(1.28)	(1.80)	(−2.12)
Hi	3.07	4.02	5.20	−2.13	−0.80	0.58	0.83	−1.63
	(2.37)	(3.21)	(4.42)	(−4.17)	(−1.90)	(1.05)	(1.32)	(−1.79)

Panel B. Bond illiquidity

	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	4.54	4.90	6.76	−2.21	−0.52	0.80	0.73	−1.25
	(3.41)	(4.06)	(3.95)	(−2.71)	(−1.17)	(1.81)	(1.25)	(−1.54)
Mid	4.22	5.15	7.31	−3.09	−0.49	0.77	1.31	−1.80
	(3.08)	(3.92)	(4.18)	(−3.03)	(−1.42)	(1.24)	(1.38)	(−1.82)
Hi	3.37	5.44	9.50	−6.14	−1.75	0.60	2.78	−4.53
	(2.11)	(3.62)	(4.70)	(−4.57)	(−3.27)	(1.05)	(2.39)	(−3.13)

Panel C. Bond dollar volume

	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	2.85	5.03	8.88	−6.02	−1.52	0.97	3.06	−4.58
	(1.97)	(3.79)	(4.73)	(−4.46)	(−2.74)	(1.76)	(2.94)	(−3.39)
Mid	4.28	4.69	6.99	−2.70	−0.44	0.55	1.22	−1.67
	(3.29)	(3.80)	(4.29)	(−3.73)	(−1.25)	(1.04)	(1.44)	(−1.78)
Hi	4.58	5.38	7.22	−2.64	−0.57	0.83	0.61	−1.18
	(3.33)	(4.04)	(3.91)	(−2.57)	(−1.26)	(1.51)	(0.83)	(−1.19)

Panel D. Bond gamma								
	Excess returns				4-factor alphas			
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	3.62	3.80	5.99	−2.36	−0.09	0.84	1.49	−1.57
	(3.35)	(3.98)	(4.46)	(−4.09)	(−0.26)	(1.88)	(2.57)	(−2.51)
Mid	4.36	5.58	7.37	−3.02	−0.90	0.80	2.00	−2.91
	(3.14)	(3.98)	(4.47)	(−3.46)	(−2.17)	(1.25)	(2.47)	(−2.86)
Hi	5.80	7.04	11.14	−5.34	−1.12	0.17	1.19	−2.31
	(2.99)	(3.70)	(3.80)	(−2.90)	(−1.39)	(0.24)	(0.97)	(−1.46)

Panel E. Number of tradedays								
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	3.71	5.48	8.80	−5.09	−1.38	0.60	2.89	−4.26
	(2.52)	(3.68)	(4.51)	(−4.19)	(−3.11)	(0.99)	(2.34)	(−3.18)
Mid	3.98	4.89	7.49	−3.51	−0.92	0.46	1.35	−2.27
	(2.81)	(3.64)	(4.35)	(−3.32)	(−2.04)	(0.85)	(1.72)	(−2.30)
Hi	4.42	5.20	7.03	−2.60	−0.51	0.96	0.71	−1.23
	(3.29)	(4.11)	(3.96)	(−2.74)	(−1.06)	(1.83)	(0.94)	(−1.17)

Table 8: **Bond illiquidity and stock DES premiums**
This table reports the average annualized value-weighted excess returns and Bai et al. (2019) four-factor abnormal returns of the debt-equity spread (DES) portfolios, conditional on different levels of average bond illiquidity. Each month we sequentially sort firms into 3-by-3 portfolios based on proxies of bond limits to arbitrage and DES. The measures of bond illiquidity include Amihud illiquidity (Amihud, 2002), dollar volume, and bond tradedays. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is monthly from August 2002 to December 2020.

Panel A. Bond Amihud illiquidity

	Excess returns				4-factor alphas			
	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	15.65	10.28	7.10	8.54	4.94	0.51	−3.82	8.76
	(4.23)	(2.74)	(1.34)	(2.91)	(2.61)	(0.39)	(−1.20)	(2.01)
Mid	11.84	7.37	5.43	6.41	2.03	−1.30	−3.82	5.85
	(3.38)	(2.53)	(1.37)	(2.95)	(1.13)	(−1.32)	(−1.93)	(1.98)
Hi	10.95	7.36	7.69	3.27	2.26	−1.87	−2.27	4.53
	(3.40)	(2.38)	(1.84)	(1.34)	(1.73)	(−1.31)	(−1.05)	(1.84)

Panel B. Bond dollar volume

	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	9.84	9.04	8.57	1.27	0.82	0.12	−1.36	2.19
	(3.05)	(3.03)	(1.95)	(0.54)	(0.69)	(0.09)	(−0.68)	(1.07)
Mid	12.39	7.98	5.71	6.68	3.03	−1.07	−4.42	7.45
	(3.87)	(2.58)	(1.21)	(2.18)	(1.46)	(−0.94)	(−1.91)	(2.15)
Hi	14.17	9.71	6.48	7.70	4.00	0.06	−3.82	7.82
	(3.40)	(3.20)	(1.46)	(2.94)	(2.27)	(0.05)	(−1.52)	(2.06)

Panel C. Bond tradedays

	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	11.57	9.23	8.07	3.50	2.82	0.37	−1.79	4.61
	(3.44)	(2.77)	(1.81)	(1.54)	(1.62)	(0.25)	(−0.75)	(1.97)
Mid	12.29	8.88	6.54	5.75	3.09	−0.12	−3.46	6.55
	(3.78)	(3.09)	(1.53)	(2.69)	(1.97)	(−0.10)	(−1.79)	(2.57)
Hi	15.56	9.62	5.71	9.84	5.15	−0.18	−4.21	9.36
	(3.74)	(2.83)	(1.35)	(3.73)	(2.75)	(−0.18)	(−2.08)	(2.63)

Table 9: **Risk factor exposure of DES portfolios**

This table reports the factor exposure of DES stock and bond portfolios. These factors include the change in monthly common idiosyncratic volatility from Herskovic et al. (2016) (dCIV), change in the monthly variance in daily market returns (dMVAR), change in monthly VIX index (dVIX), jump risk (Jump), measured as the change in the implied volatility of the deep out-of-the-money Standard and Poor's (S&P) 500 put options following Benzoni et al. (2011), two measures of investment-specific technology shocks,(i.e., investment-minus-consumption portfolio return (IMC) from Kogan and Papanikolaou (2014) and the negative change in equipment price relative to nondurable consumption goods price (Ishock)), and change in 10-year government bond yield (dYld). For each of these factors, we test the DES portfolios on a two-factor model with this factor along with the market factor and report its coefficient. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. Panel A reports the results for DES stock portfolios, and Panel B reports the results for DES bond portfolios. The sample is monthly from January 1980 to December 2020 for dCIV, dMVAR, IMC, and dYld, monthly from March 1990 to December 2020 for dVIX, monthly from January 1996 to December 2020 for Jump, and annual from 1980 to 2020 for Ishock.

Panel A. Stock returns						
	L(ow)	2	3	4	H(igh)	L-H
dCIV	0.36	0.25	−0.30	−0.77	−1.39	1.75
	(0.98)	(0.80)	(−1.48)	(−2.22)	(−4.83)	(3.82)
dMVAR	0.06	0.04	−0.02	−0.12	−0.12	0.18
	(1.56)	(1.99)	(−1.13)	(−3.67)	(−3.77)	(4.29)
dVIX	−0.06	−0.09	−0.03	−0.04	−0.07	0.02
	(−1.24)	(−2.80)	(−0.94)	(−1.00)	(−1.19)	(0.26)
Jump	0.18	−2.00	−1.51	−1.46	−0.96	1.14
	(0.18)	(−2.15)	(−2.39)	(−1.65)	(−0.58)	(0.70)
IMC	−4.05	−9.52	−7.54	−12.11	0.34	−4.39
	(−0.68)	(−2.30)	(−2.83)	(−3.25)	(0.07)	(−0.80)
Ishock	0.32	0.09	−0.05	−0.36	0.02	0.30
	(0.83)	(0.36)	(−0.24)	(−0.77)	(0.03)	(0.50)
dYld	0.59	0.10	−0.44	−0.72	−0.09	0.68
	(1.44)	(0.40)	(−1.80)	(−2.08)	(−0.30)	(1.21)

Panel B. Bond returns						
	L(ow)	2	3	4	H(igh)	L-H
dCIV	−0.06	0.54	0.52	0.14	−0.94	0.89
	(−0.68)	(3.35)	(4.97)	(1.40)	(−3.37)	(3.38)
dMVAR	−0.01	0.06	0.07	0.02	−0.14	0.13
	(−1.07)	(2.63)	(4.35)	(2.11)	(−3.60)	(3.61)
dVIX	−0.05	−0.01	0.01	−0.01	−0.12	0.07
	(−3.60)	(−1.25)	(1.16)	(−1.27)	(−5.54)	(2.77)
Jump	−1.08	−0.29	0.20	−0.30	−2.93	1.85
	(−2.76)	(−1.20)	(1.01)	(−1.09)	(−4.91)	(2.86)
IMC	1.56	−1.48	−1.43	−0.32	8.58	−7.02
	(1.06)	(−1.26)	(−1.25)	(−0.28)	(3.58)	(−3.38)
Ishock	−0.07	0.32	0.23	0.23	−0.03	−0.04
	(−0.21)	(0.89)	(1.21)	(2.18)	(−0.05)	(−0.05)
dYld	−0.36	−0.85	−0.89	−0.44	0.53	−0.89
	(−1.56)	(−2.15)	(−2.67)	(−1.99)	(1.45)	(−2.63)

Table 10: **Long-term earnings growth forecast revisions**

This table examines the relation between the debt-equity spread (DES) and long-term earnings growth forecasts (LTG), which are obtained from the Institutional Brokers Estimate System (IBES) Summary unadjusted file. Panel A reports the average LTG for the DES quintiles. t(diff) is the Newey-West t-statistic for the difference in the average LTG between high and low DES quintiles, based on a lag of 12 months. Panel B reports the coefficients of DES in the Fama-MacBeth regressions in predicting future 12-, 24-, 36-, 48-, 60-month cumulative changes in LTG. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of K+2, where K is the predictive horizon. The sample is monthly from January 1981 to December 2020.

Panel A. Average LTG

L(ow)	2	3	4	H(igh)	t(diff)
10.21	11.59	11.68	12.12	12.73	(9.06)

Panel B. FMB of future LTG changes on DES

	(K=) 12	24	36	48	60
DES	−0.00	−0.15	−0.21	−0.28	−0.32
	(−0.04)	(−2.58)	(−3.35)	(−3.31)	(−3.02)

Table 11: **Corporate security issuance and cash holdings**

This table examines the relation between debt-equity spread (DES) and corporate financial policies. Panel A reports results from panel regressions of quarterly net equity issuance, net debt issuance, debt-equity swap, and change in cash holdings on the DES, actual credit spread (CS^D), and market-to-book equity ratio (ME/BE) of the previous quarter. Panel B reports results from logistic regressions of equity issuance for debt retirement (equity-debt swap) and indicators of cash reduction for debt retirement on the same set of key independent variables. We include standard control variables of the previous quarter, namely, leverage, the logarithm of total assets, profitability, tangibility, cash reserve and dividend payout. We control for firm and time fixed effects across all specifications for panel regressions in Panel A. We demean all the variables at the firm level and control for time fixed effect for logistic regressions in Panel B. The variable definitions are in Panel C of Table 1. We report t-statistics for the panel regressions and z-statistics for logistic regressions in parentheses, and adjust the t-statistics using standard errors clustered at the firm level. The sample is quarterly from 1980 to 2020.

Panel A. Panel regressions

	Net equity issuance			Net debt issuance			Change in cash holdings		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
DES		0.09	0.12		−0.15	−0.26		−0.11	−0.23
		(3.46)	(4.08)		(−2.51)	(−3.93)		(−1.91)	(−3.69)
ME/BE	0.06	0.07	0.06	−0.16	−0.17	−0.16	0.04	0.03	0.04
	(1.42)	(1.49)	(1.45)	(−2.26)	(−2.39)	(−2.31)	(0.46)	(0.35)	(0.43)
CS^D	−0.05		−0.10	0.30		0.42	0.36		0.46
	(−1.66)		(−2.92)	(4.23)		(5.14)	(4.81)		(5.43)
MktLev	0.04	0.04	0.05	−0.23	−0.23	−0.25	−0.07	−0.06	−0.09
	(8.43)	(9.06)	(9.26)	(−18.66)	(−18.57)	(−17.51)	(−6.71)	(−5.68)	(−7.32)
log(BA)	−0.01	−0.01	−0.01	−0.02	−0.02	−0.02	−0.03	−0.03	−0.03
	(−5.53)	(−5.49)	(−5.68)	(−6.11)	(−6.76)	(−5.85)	(−8.65)	(−9.19)	(−8.43)
Profitability	−0.13	−0.13	−0.13	−0.30	−0.32	−0.30	−0.07	−0.09	−0.07
	(−4.70)	(−4.57)	(−4.66)	(−3.68)	(−3.86)	(−3.70)	(−0.58)	(−0.71)	(−0.59)
Tangibility	0.01	0.01	0.01	0.08	0.08	0.07	−0.03	−0.03	−0.03
	(1.31)	(1.33)	(1.35)	(4.91)	(4.95)	(4.86)	(−1.71)	(−1.70)	(−1.75)
Cash	−0.05	−0.05	−0.05	−0.12	−0.12	−0.13	−0.95	−0.95	−0.95
	(−4.82)	(−4.80)	(−4.62)	(−5.03)	(−4.96)	(−5.18)	(−15.63)	(−15.67)	(−15.57)
Dividend	−0.15	−0.15	−0.15	0.54	0.54	0.56	0.11	0.10	0.12
	(−2.38)	(−2.41)	(−2.49)	(6.52)	(6.44)	(6.69)	(1.01)	(0.89)	(1.12)
N_obs	46071	46071	46071	46071	46071	46071	46071	46071	46071
Adj. R^2	0.19	0.19	0.19	0.07	0.07	0.07	0.10	0.10	0.10

Panel B. Logistic regressions						
	Equity-debt swap			Draw down cash to retire debt		
	(1)	(2)	(3)	(1)	(2)	(3)
DES		2.82	5.34		1.45	2.99
		(3.20)	(5.56)		(1.73)	(3.34)
ME/BE	0.05	0.05	0.05	−0.01	−0.01	−0.01
	(4.89)	(4.89)	(5.12)	(−0.85)	(−0.86)	(−0.72)
$\mathrm{CS^D}$	−6.98		−9.08	−4.68		−5.84
	(−6.30)		(−7.75)	(−4.49)		(−5.31)
MktLev	1.99	1.76	2.36	2.10	1.93	2.30
	(13.96)	(12.84)	(14.98)	(15.67)	(14.91)	(15.61)
log(BA)	−0.00	0.00	−0.01	0.16	0.17	0.16
	(−0.16)	(0.16)	(−0.20)	(6.16)	(6.42)	(6.16)
Profitability	0.07	0.40	0.12	2.20	2.42	2.23
	(0.10)	(0.58)	(0.18)	(3.42)	(3.76)	(3.46)
Tangibility	−0.72	−0.70	−0.73	−0.66	−0.64	−0.66
	(−3.76)	(−3.65)	(−3.81)	(−3.63)	(−3.53)	(−3.65)
Cash	0.03	−0.13	0.16	7.41	7.29	7.48
	(0.12)	(−0.48)	(0.60)	(29.66)	(29.43)	(29.81)
Dividend	−6.06	−5.85	−6.39	−4.91	−4.78	−5.08
	(−4.59)	(−4.44)	(−4.83)	(−4.05)	(−3.95)	(−4.18)
N_obs	46178	46178	46178	46178	46178	46178
Pseudo R^2	0.01	0.01	0.01	0.03	0.02	0.03

Table 12: **Insider stock selling**

This table reports results from panel regressions of monthly insider sales on the debt-equity spread (DES), actual credit spread (CS^D), and market-to-book equity ratio (ME/BE) of the previous quarter. We use two measures to proxy for insider selling activities, including the fraction of insider sales volume (the number of shares sold divided by the total number of shares traded each month) and the fraction of insider sales (the number of sales divided by the total number of trades each month). We then merge monthly insider trading measures with our DES measure as well as quarterly Compustat data. We follow Guay et al. (2021) and include standard control variables of the previous quarter, namely, the logarithm of total assets, profitability, book leverage, and market-to-book equity ratio (ME/BE). We include firm and time fixed effects in all specifications. The variable definitions are in Panel C of Table 1. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. The sample is quarterly from 1986 to 2019, except for Specification (3), where the sample ends in 2016 because of the data availability of MispScore.

	Fraction of insider sales volume			Fraction of insider sales		
	(1)	(2)	(3)	(1)	(2)	(3)
DES	2.14	1.93	1.56	2.12	1.92	1.55
	(5.00)	(4.43)	(3.05)	(4.97)	(4.43)	(3.03)
CS^D	−4.44	−4.09	−3.76	−4.37	−4.04	−3.66
	(−10.06)	(−9.18)	(−7.06)	(−9.62)	(−8.80)	(−6.75)
ME/BE		0.01	0.01		0.01	0.01
		(4.18)	(2.57)		(3.98)	(2.40)
log(BA)	−0.03	−0.02	−0.03	−0.04	−0.02	−0.04
	(−2.24)	(−1.19)	(−1.87)	(−2.42)	(−1.41)	(−2.07)
Profitability	0.01	0.01	0.01	0.01	0.00	0.01
	(0.37)	(0.28)	(0.62)	(0.31)	(0.22)	(0.60)
Lev	−0.06	−0.15	−0.14	−0.07	−0.15	−0.14
	(−1.08)	(−2.51)	(−2.02)	(−1.09)	(−2.45)	(−1.97)
MispScore			−0.16			−0.16
			(−3.39)			(−3.40)
N_obs	14479	14479	12199	14479	14479	12199
Adj. R^2	0.38	0.38	0.34	0.38	0.38	0.34

Internet Appendix for "The Debt-Equity Spread"

Hui Chen Zhiyao Chen Jun Li

A Bond data

A.1 Filters

We restrict our sample to semi-annual and unsecured senior bonds and apply the following filters from FISD Mergent:

1. Remove bonds that are not listed or traded in the US public market, which include bonds issued through private placement, bonds issued under the 144A rule, bonds that do not trade in US dollars, and bond issuers not in the jurisdiction of the United States.

2. Remove bonds that are structured notes, mortgage backed or asset backed, agency backed or equity linked.

3. Remove convertible bonds since this option feature distorts the return calculation and makes it impossible to compare the returns of convertible and nonconvertible bonds.

4. Remove bonds that trade under one dollar or above one thousand dollars.

5. Remove bonds that have a floating coupon rate, and keep bonds with a fixed or zero coupon rate.

6. Remove bonds that have less than one year to maturity. If a bond has less than one year to maturity, it will be delisted from major bond indices; hence, index-tracking investors will change their holding positions. This operation will distort the return calculation for bonds with less than one year to maturity.

7. Eliminate bond transactions that are labeled as when-issued, locked-in, or with special sales conditions.

A.2 Calculation of bond returns

We use bond returns from Lehman Brothers Fixed Income Database for the period January 1980 to June 1998, and RET_L5M from Wharton Research Data Services (WRDS) for the period July 2002 to December 2020. For the rest of the sample, we use bond prices from NAIC and calculate the monthly excess bond returns as follows:

$$r_{i,t}^B = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1 - r_{f,t}, \tag{A.1}$$

where $P_{i,t}$ is the transaction price, $AI_{i,t}$ is accrued interest, $C_{i,t}$ is the coupon payment, if any, of bond i in month t, and $r_{f,t}$ is the risk-free rate proxied by the one-month Treasury bill rate. We convert the daily bond prices into monthly prices. Following Bai et al. (2019), we identify two scenarios for a return to be realized at the end of month t: (i) from the end of month $t-1$ to the end of month t and (ii) from the beginning of month t to the end of month t. We calculate monthly returns for both scenarios, where the end (beginning) of the month refers to the last (first) five trading days within each month. If there are multiple trading records in the five-day window, the one closest to the last trading day of the month is selected. For the second scenario, we use the first available price within the first five-day window as the beginning price of the month. We choose the realized return in scenario one (from month-end $t-1$ to month-end t) when monthly returns are available in both scenarios.

B Robustness tests

B.1 Subsample analyses

We formally test the stability of the DES return prediction using subsample analyses. We use the end of 1999 as the midpoint and split the full sample period into two subsamples. Panel A of Table B1 shows that, despite the shorter time series in each subsample, the long-short portfolio generates large negative returns in both samples and for both weighting schemes. The average annualized value-weighted (equal-weighted) stock return is 7.74% (7.32%) from January 1980 to December 1999 and 7.71% (8.51%) from January 2000 to December 2020. Moreover, the abnormal returns from the Carhart four-factor model, α^{C4}, increase from the raw return spreads in both subsamples.

[Insert Table B1 here]

We find similarly stable return predictions across the subsamples for bonds in Panel B. The average annualized value-weighted (equal-weighted) bond return is -4.32% (-5.33%) from January 1980 to December 1999 and -5.58% (-7.32%) from January 2000 to December 2020. After controlling for the bond market factor, the abnormal bond returns, α^{mkt}, remain economically and statistically significant.

B.2 Black-Cox model-based DES

The benchmark DES we use in the paper is constructed based on the extended CreditGrades model, which is adapted to better match the empirical credit spread. One may wonder how our asset pricing results change when we use the simple Black-Cox model without the stochastic default boundary. We report the results of this analysis in Table B2.

[Insert Table B2 here]

Without the stochastic default boundary, the model generates a model-implied credit spread of only 118.7 basis points (untabulated), less than half of the empirical credit spread, which echoes the credit spread puzzle in the literature. However, the predictions of DES on the cross-sectional stock and bond returns are quite robust. For example, with the value-weighted scheme, the average Lo-Hi DES quintile has an annualized return of 7.62% in the stock portfolios and −3.86% in the bond portfolios. These results are quantitatively consistent with those using the benchmark DES. Therefore, our asset pricing results are not sensitive to the specific credit risk model in constructing DES.

B.3 Industry-adjusted DES and returns

To alleviate the concern that our results are driven by unobservable heterogeneity across industries, such as industry-specific competition and recovery rates, we sort firms into quintile portfolios based on the industry-adjusted DES. At each month, we adjust DES for industry by taking the difference between a firm's DES and its affiliated industry median DES. We use the Fama and French 12-industry classification because the number of firms at the beginning of our sample is small. For example, the number of firms available in 1980 is about 60 per month, which increases to more than 500 firms per month in 2010.

[Insert Table B3 here]

We first report the results on stock returns. As shown in Panel A of Table B3, the industry-adjusted DES premium remains economically large and statistically significant for both value- and equal-weighted portfolios. For example, the annualized value-weighted DES premium is 7.53% (t-statistic = 4.55), and the Carhart four-factor alpha is 8.02% (t-statistic = 4.44), respectively. When turning to the bond returns in Panel B,we see that the value- and equal-weighted bond returns of the L-H portfolio are –5.57 (t-statistic = –6.57) and –7.8 (t-statistic = –6.87), respectively.

As such, the estimates of the DES premium in stock and bond returns mostly become larger after we control for the industry effects.

B.4 CDS trading and DES premiums

We examine the relation between CDS trading and DES premiums in Table B4. The literature documents that the introduction of CDS can affect bond liquidity and market efficiency (e.g., Das et al. (2014)). It can also create information flow between the equity and CDS markets.

For instance, Acharya and Johnson (2007) find that changes in CDS spreads negatively predict stock returns, giving rise to a lead-lag linkage between these two markets.

[Insert Table B4 here]

However, the results in Table B4 indicate that the DES premiums remain strong in both subsamples with and without CDS trading. In Panel A, the annualized stock DES premium is 7.51% for the subsample with CDS trading, as compared with 9.53% for the subsample without CDS trading. Similarly, the bond DES premiums are both around 4%-5% per year. Therefore, despite the impact of CDS trading on bond and equity markets documented in the literature, the DES premiums are not significantly affected by CDS tradings.

B.5 Time to maturity and bond DES premium

To further examine the role of jump risk exposure to the DES premium, we double-sort bonds into time to maturity and DES. Bai et al. (2020) document that short-maturity bonds are more exposed to jump risk than long-maturity bonds. If jump risk is an important driver for the DES premiums, we expect the DES bond return spreads to be stronger among short-maturity bonds. However, Table B5 shows that this is not the case. In our sample from 1980 to 2020, the bond DES premium is –3.7% for long-maturity bonds, which is higher than –3.09% for short-maturity bonds. The result remains after we control for the Bai et al. (2019) factors.

[Insert Table B5 here]

B.6 Relation to capital structure arbitrage

In the main text, we separately uncover the robust predictive power of DES on cross-sectional stock and bond returns. The opposite signs of the stock and bond return predictions suggest that investors could combine these two asset classes to achieve an even better risk-return trade-off, an idea closely related to the so-called capital structure arbitrage, in which investors exploit the relative price difference of securities of the same firms. In this subsection, we analyze the performance of this strategy in our sample.

A capital structure arbitrage strategy uses an estimated hedge ratio to form hedged portfolios, which is expected to eliminate underlying asset risk for risk-free profits. Because the estimated hedge ratio depends on a specific credit risk model, it potentially suffers from model misspecifications and measurement errors and thus residual exposure to both idiosyncratic and systematic asset risks. Schaefer and Strebulaev (2008) argue that, although credit risk models such as Merton (1974) might underestimate credit spreads because of the missing liquidity component, they provide "quite accurate predictions of the sensitivity of corporate bond returns to changes in the value of equity (hedge ratios)" because the bond price change is mostly driven by changing asset values. As such, we follow Schaefer and Strebulaev (2008) and construct the bond-level hedge ratio, η, using our CreditGrades model.[23]

To implement the capital structure arbitrage strategy, we short-sell $\$\eta$ of stock for each dollar of bonds purchased. The return from this strategy, $r^H = r^D - \eta r^S$, is expected to have zero exposure to asset risk, where r^D and r^S are bond and stock returns, respectively. In the context of our analyses, if r^H reflects the correction of relative mispricing between the stock and bond markets, and if DES captures the strength of relative mispricing, we expect average r^H to increase with DES. To test this prediction, we sort bonds in our sample into quintiles based on their DES and compute the average portfolio hedged return r^H. Table B6 reports the average r^H, the abnormal return from the CAPM model with both stock market and bond market factors, and the abnormal return from a seven-factor model with three equity factors from Fama and French (1992) and four bond factors from Bai et al. (2019) for each DES quintile. Panel A shows the value-weighted result, where the weights are based on the lagged bond value.[24] Consistent with our conjecture, the average hedged return increases strongly with DES. The average hedged return is −0.21% per year for the low-DES quintile, as compared to 7.35% per year for the high-DES quintile. Their difference is more than seven standard deviations from zero.

[Insert Table B6 here]

It is worth noting that the t-statistic in the H-L portfolio is larger than the t-statistic of the individual DES quintiles. This is likely a result of the residual asset risk, especially the systematic risk, in the hedged position. Yu (2006) shows that grouping the hedged positions of different firms into portfolios can diversify idiosyncratic asset risks and improve the Sharpe ratio. Our result takes one step further and highlights that a long-short position between the

[23] We use the central difference scheme (i.e., $\frac{E\Delta D}{D\Delta E} = \frac{E}{D}\frac{(D(E+\Delta E))-D(E-\Delta E))}{2\Delta E}$) to calculate the bond-level hedge ratio numerically by perturbing the input equity value in the extended CreditGrades model. In untabulated results, we follow Schaefer and Strebulaev (2008) and validate our hedge ratio measure. By regressing excess bond returns on the product of the hedge ratio and excess stock returns, we find the estimated coefficients are close to one.

[24] The average hedged returns are positive for all portfolios except for the low-DES quintile. This is likely because r^H does not completely hedge out all asset risks resulting from model misspecifications or measurement errors described above, and the positive average returns may reflect the premiums associated with the remaining systematic risk exposure. Indeed, we find that the betas of all DES quintiles to the bond market factor are very close to one in untabulated results, and after controlling for the bond and equity factors, the average abnormal hedged return across DES quintiles is much closer to zero.

high- and low-DES hedged quintiles could reduce the remaining systematic risk exposure and achieve an even better risk-return trade-off.

The pattern is similar when we control for equity and bond factors and when we use equal-weighted portfolios (Panel B, Table B6). Taken together, our findings on the stock and bond return predictions of DES can be used to improve the performance of the capital structure arbitrage strategy.

B.7 DES and corporate issuances using alternative control variables

Profitability is an important determinant of capital structure in the tradeoff theory. We follow Ma (2019) and include profitability and capital investments of the contemporaneous quarter as our control variables. As shown in Table B7, our results are robust to different timing of control variables.

[Insert Table B7 here]

B.8 DES and corporate investments

We provide further evidence on corporate investments, including capital and research and development (R&D) investments in Table B8. Different from the results in Table 11, most of the coefficients of DES are economically and statistically insignificant. The difference indicates that, although they might take advantage of the mispricing of financial securities of their own companies, which are less costly to adjust, the managers do not change their long-term physical and R&D investment decisions.

[Insert Table B8 here]

B.9 DES and insider trading

We report additional tests to validate our measure via corporate insider trading in Table B9.

[Insert Table B9 here]

We use a larger sample that includes "routine" trades (Cohen et al., 2012). The estimated coefficients of DES are similar to those in Table 12. Therefore, our results are independent of sample selection.

Table B1: **Subsample analysis**

This table reports the average annualized excess returns and abnormal returns of DES stock portfolios (Panel A) and bond portfolios (Panel B) for the subperiods of 1980-1999 and 2000-2020. In Panel A, we form stock quintile portfolios based on the firm-level debt-equity spread (DES) of the previous month and then estimate the stock alphas from CAPM, Carhart four-factor model (C4), and Stambaugh and Yuan (2017) mispricing factor model (M4). In Panel B, we form bond quintile portfolios based on the bond-level DES of the previous month and then estimate the one-factor bond alphas, α^{mkt}, by regressing excess bond returns on an intercept and the market bond returns (proxied by the Merrill Lynch Index) and estimate the four-factor bond alphas, α^{4F}, by regressing the excess bond returns on an intercept and four bond factors in Bai et al. (2019) for the period July 2004 to June 2019. The full samples are described in Table 3, with the end of 1999 as the cutoff date for the two subsamples. We report the results using both the value-weighted (VW) scheme and the equal-weighted (EW) scheme.The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12.

Panel A: Stock portfolios

VW Returns from 1980 to 1999						
	L(ow)	2	3	4	H(igh)	L-H
mean	13.34	10.88	8.49	10.83	5.61	7.74
	(4.41)	(3.99)	(2.80)	(3.17)	(1.78)	(3.37)
α^{CAPM}	3.15	1.37	−1.65	0.34	−4.85	8.01
	(1.73)	(0.81)	(−1.25)	(0.23)	(−2.84)	(3.35)
α^{C4}	2.76	1.27	−1.16	0.05	−5.62	8.37
	(1.72)	(0.61)	(−0.80)	(0.03)	(−3.42)	(3.27)
α^{M4}	3.61	0.10	−3.22	−1.99	−7.14	10.76
	(2.03)	(0.04)	(−2.08)	(−1.04)	(−3.01)	(3.39)

VW Returns from 2000 to 2020						
	L(ow)	2	3	4	H(igh)	L-H
mean	11.28	8.19	5.11	4.12	3.57	7.71
	(2.55)	(2.51)	(1.58)	(1.05)	(0.73)	(2.73)
α^{CAPM}	4.47	2.51	−0.27	−1.39	−3.65	8.12
	(2.09)	(2.03)	(−0.22)	(−0.96)	(−1.52)	(2.70)
α^{C4}	5.25	3.07	0.10	−1.38	−3.38	8.63
	(3.17)	(2.31)	(0.08)	(−0.98)	(−1.43)	(2.68)
α^{M4}	5.14	2.74	−0.31	−1.41	−1.61	6.75
	(1.98)	(1.60)	(−0.22)	(−0.69)	(−0.52)	(1.46)

EW Returns from 1980 to 1999						
	L(ow)	2	3	4	H(igh)	L-H
mean	13.18	10.85	8.80	10.52	5.86	7.32
	(3.97)	(3.79)	(2.86)	(3.06)	(1.73)	(3.27)
α^{CAPM}	2.20	0.71	−1.56	−0.47	−5.21	7.41
	(1.06)	(0.45)	(−1.15)	(−0.38)	(−2.36)	(3.27)
α^{C4}	3.38	1.37	−0.47	−0.33	−4.17	7.55
	(2.32)	(0.95)	(−0.39)	(−0.27)	(−2.33)	(2.95)
α^{M4}	4.43	0.38	−1.66	−2.73	−5.82	10.25
	(2.82)	(0.25)	(−1.07)	(−2.14)	(−2.87)	(3.87)

EW Returns from 2000 to 2020						
	L(ow)	2	3	4	H(igh)	L-H
mean	16.72	12.26	8.32	7.71	8.21	8.51
	(3.10)	(3.46)	(2.43)	(2.01)	(1.60)	(2.97)
α^{CAPM}	8.06	5.64	2.38	1.13	−0.72	8.78
	(2.17)	(2.49)	(1.16)	(0.57)	(−0.23)	(2.91)
α^{C4}	8.58	5.85	2.44	1.13	−0.31	8.89
	(4.35)	(3.97)	(2.11)	(1.07)	(−0.14)	(2.93)
α^{M4}	11.39	5.78	2.01	1.07	2.74	8.65
	(3.40)	(2.60)	(1.73)	(0.71)	(1.08)	(2.14)

Panel B: Bond portfolios

VW Returns from 1980 to 1999						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.04	2.58	3.45	3.80	6.36	−4.32
	(0.91)	(1.11)	(1.60)	(1.82)	(3.67)	(−4.11)
α^{mkt}	−1.71	−1.50	−0.56	0.10	3.16	−4.86
	(−3.47)	(−4.70)	(−2.05)	(0.19)	(4.17)	(−5.72)

VW Returns from 2000 to 2020						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.78	4.10	4.96	5.82	8.36	−5.58
	(1.83)	(3.24)	(4.29)	(4.74)	(4.48)	(−3.92)
α^{mkt}	−1.51	−0.14	0.83	1.59	3.31	−4.82
	(−1.52)	(−0.20)	(1.35)	(3.25)	(2.88)	(−3.27)

EW Returns from 1980 to 1999						
	L(ow)	2	3	4	H(igh)	L-H
mean	1.68	2.41	3.68	4.31	7.01	−5.33
	(0.77)	(1.02)	(1.70)	(2.10)	(3.79)	(−5.30)
α^{mkt}	−1.90	−1.57	−0.28	0.60	3.81	−5.71
	(−3.57)	(−4.07)	(−1.01)	(1.27)	(5.14)	(−6.16)

EW Returns from 2000 to 2020						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.89	3.76	4.68	5.73	10.20	−7.32
	(1.91)	(2.90)	(4.05)	(4.65)	(4.81)	(−4.59)
α^{mkt}	−1.31	−0.25	0.63	1.56	5.10	−6.41
	(−1.34)	(−0.35)	(1.31)	(3.62)	(4.14)	(−4.26)

Table B2: **Black-Cox model-based DES**

This table reports average annualized excess returns and abnormal returns for stocks and bonds using the Black-Cox model-based DES. In Panel A, we form stock quintile portfolios based on the firm-level debt-equity spread (DES) of the previous month based on the Black-Cox model and then estimate the stock alphas from CAPM, Fama and French (1992) three-factor model (FF3), Carhart four-factor model (C4), Fama and French (2015) five-factor model (FF5), Stambaugh and Yuan (2017) mispricing factor model (M4), and Hou, Xue, and Zhang (2015) q-factor model (HXZ). In Panel B, we form the bond quintile portfolios based on the bond-level DES of the previous month and then estimate the one-factor bond alphas, α^{mkt}, by regressing excess bond returns on an intercept and the market bond returns (proxied by the Merrill Lynch Index) and estimate the four-factor bond alphas, α^{4F}, by regressing the excess bond returns on an intercept and four bond factors proposed by Bai et al. (2019). The sample is from January 1980 to December 2020, except for the bond four-factor model tests, where the sample period is from July 2004 to December 2019 owing to the availability of the Bai et al. (2019) factors. We report the results using both the value-weighted (VW) scheme and the equal-weighted (EW) scheme. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12.

Panel A: Stock returns

	VW Returns					
	L(ow)	2	3	4	H(igh)	L-H
mean	12.75	7.66	8.15	5.90	5.13	7.62
	(5.13)	(3.56)	(3.30)	(2.31)	(1.56)	(3.91)
α^{CAPM}	4.32	−0.04	0.44	−1.95	−4.19	8.51
	(3.29)	(−0.04)	(0.50)	(−1.42)	(−2.76)	(4.14)
α^{FF3}	3.44	−0.22	0.33	−2.74	−5.00	8.44
	(2.73)	(−0.26)	(0.38)	(−2.48)	(−3.40)	(3.97)
α^{C4}	4.56	−0.33	0.76	−2.58	−3.70	8.25
	(3.71)	(−0.40)	(0.90)	(−2.35)	(−2.71)	(3.96)
α^{FF5}	2.74	−1.72	−1.70	−4.12	−5.14	7.88
	(2.23)	(−2.14)	(−1.72)	(−3.73)	(−3.38)	(3.82)
α^{M4}	4.30	−1.10	−0.43	−2.64	−3.05	7.35
	(2.95)	(−1.13)	(−0.41)	(−1.88)	(−1.92)	(3.14)
α^{HXZ}	3.35	−1.24	−0.54	−2.36	−3.19	6.54
	(2.30)	(−1.31)	(−0.47)	(−1.65)	(−1.77)	(2.71)

EW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	15.70	9.91	9.69	8.18	7.47	8.23
	(5.17)	(4.17)	(4.16)	(3.13)	(2.28)	(4.34)
α^{CAPM}	5.94	1.60	1.50	−0.65	−3.14	9.09
	(2.90)	(1.14)	(1.19)	(−0.39)	(−1.50)	(4.59)
α^{FF3}	4.24	0.62	0.68	−1.95	−4.86	9.09
	(2.54)	(0.50)	(0.67)	(−1.81)	(−3.01)	(4.25)
α^{C4}	6.37	1.36	1.73	−1.04	−2.18	8.55
	(3.74)	(1.28)	(1.92)	(−1.04)	(−1.57)	(3.84)
α^{FF5}	2.92	−1.54	−1.41	−3.65	−5.66	8.58
	(1.94)	(−1.31)	(−1.52)	(−3.63)	(−3.33)	(4.33)
α^{M4}	6.50	−0.16	0.38	−1.57	−1.99	8.49
	(3.09)	(−0.10)	(0.32)	(−1.25)	(−1.13)	(3.64)
α^{HXZ}	4.97	−0.72	−0.24	−1.58	−2.51	7.48
	(2.72)	(−0.42)	(−0.16)	(−1.01)	(−1.03)	(2.73)

Panel B: Bond returns

VW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.74	3.97	4.16	4.79	6.60	−3.86
	(1.95)	(3.03)	(3.45)	(4.14)	(5.11)	(−4.25)
α^{mkt}	−1.70	−0.58	−0.02	0.76	2.74	−4.44
	(−3.16)	(−1.46)	(−0.06)	(1.85)	(3.79)	(−5.01)
α^{4f}	−0.73	0.26	0.69	0.77	1.47	−2.20
	(−1.69)	(0.54)	(1.41)	(1.24)	(1.50)	(−1.88)

EW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.84	3.75	4.06	5.06	7.81	−4.97
	(2.06)	(2.87)	(3.35)	(4.40)	(5.51)	(−5.38)
α^{mkt}	−1.51	−0.63	−0.12	1.07	3.95	−5.46
	(−3.21)	(−1.65)	(−0.34)	(2.61)	(5.18)	(−6.20)
α^{4f}	−0.74	0.13	0.54	1.16	1.78	−2.52
	(−1.53)	(0.25)	(1.18)	(1.90)	(2.00)	(−2.40)

Table B3: **Industry-adjusted DES**

This table reports average annualized excess returns and abnormal returns for industry-adjusted DES stock and bond portfolios. We use the Fama and French 12-industry classification and adjust for industry by taking the difference between the firm-level DES and industry median DES at each month. In Panel A, we form stock quintile portfolios based on the industry-adjusted DES of the previous month and then estimate the stock alphas from CAPM, Fama and French (1992) three-factor model (FF3), Carhart four-factor model (C4), Fama and French (2015) five-factor model (FF5), Stambaugh and Yuan (2017) mispricing factor model (M4), and Hou, Xue, and Zhang (2015) q-factor model (HXZ). In Panel B, we form bond quintile portfolios based on the bond-level industry-adjusted DES of the previous month and then estimate the one-factor bond alphas, α^{mkt}, by regressing excess bond returns on an intercept and the market bond returns (proxied by the Merrill Lynch Index) and estimate the four-factor bond alphas, α^{4F}, by regressing the excess bond returns on an intercept and four bond factors proposed by Bai et al. (2019). We report the results using both the value-weighted (VW) scheme and the equal-weighted (EW) scheme. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is from January 1980 to December 2020, except for the bond four-factor model tests, where the sample period is from July 2004 to December 2019 owing to the availability of the Bai et al. (2019) factors.

Panel A: Stock portfolios

	VW Returns					
	L(ow)	2	3	4	H(igh)	L-H
mean	12.53	9.52	6.39	7.09	5.00	7.53
	(4.79)	(4.20)	(2.56)	(2.92)	(1.75)	(4.55)
α^{CAPM}	3.87	1.94	−1.06	−0.44	−3.73	7.60
	(2.82)	(1.68)	(−0.90)	(−0.38)	(−2.76)	(4.21)
α^{FF3}	2.87	1.87	−1.12	−0.91	−4.36	7.23
	(2.19)	(1.72)	(−1.03)	(−0.88)	(−3.57)	(3.92)
α^{C4}	4.49	2.03	−0.96	−1.02	−3.53	8.02
	(3.66)	(1.74)	(−0.90)	(−1.01)	(−2.84)	(4.44)
α^{FF5}	1.93	0.44	−2.69	−2.84	−4.74	6.68
	(1.41)	(0.44)	(−2.15)	(−2.84)	(−3.51)	(3.36)
α^{M4}	4.33	−0.02	−1.68	−1.46	−2.55	6.88
	(2.72)	(−0.02)	(−1.30)	(−1.25)	(−1.58)	(3.08)
α^{HXZ}	3.58	0.22	−1.91	−1.78	−2.26	5.84
	(1.99)	(0.20)	(−1.42)	(−1.62)	(−1.43)	(2.59)

EW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	14.95	11.00	9.94	7.74	7.62	7.32
	(4.52)	(4.54)	(4.50)	(3.10)	(2.49)	(4.34)
α^{CAPM}	4.71	2.52	2.01	−0.85	−2.59	7.30
	(2.13)	(1.78)	(1.72)	(−0.61)	(−1.32)	(4.07)
α^{FF3}	2.90	1.53	1.23	−1.98	−4.11	7.00
	(1.75)	(1.30)	(1.25)	(−1.99)	(−2.86)	(3.66)
α^{C4}	5.87	2.46	2.06	−1.17	−1.92	7.79
	(3.76)	(2.37)	(2.69)	(−1.24)	(−1.48)	(3.92)
α^{FF5}	1.91	−0.39	−1.07	−3.80	−4.74	6.65
	(1.13)	(−0.36)	(−1.14)	(−4.15)	(−3.07)	(3.67)
α^{M4}	6.31	1.01	0.57	−2.29	−1.25	7.56
	(3.08)	(0.70)	(0.52)	(−1.84)	(−0.77)	(3.23)
α^{HXZ}	5.04	0.31	−0.20	−2.33	−1.60	6.64
	(2.19)	(0.21)	(−0.14)	(−1.81)	(−0.72)	(2.83)

Panel B: Bond portfolios

VW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	2.43	2.84	3.63	5.28	7.99	−5.57
	(1.90)	(2.36)	(3.10)	(4.62)	(5.76)	(−6.57)
α^{mkt}	−1.32	−1.07	−0.25	1.40	4.33	−5.65
	(−2.31)	(−2.31)	(−0.56)	(3.04)	(5.86)	(−7.20)
α^{4f}	−0.02	0.11	0.84	1.94	2.63	−2.64
	(−0.03)	(0.21)	(1.77)	(4.19)	(3.22)	(−4.08)

EW Returns						
	L(ow)	2	3	4	H(igh)	L-H
mean	1.90	2.92	3.58	5.52	9.70	−7.80
	(1.45)	(2.34)	(3.15)	(4.77)	(6.06)	(−6.87)
α^{mkt}	−1.73	−0.96	−0.25	1.69	5.95	−7.68
	(−2.57)	(−2.36)	(−0.68)	(3.65)	(6.75)	(−7.42)
α^{4f}	−0.65	−0.33	0.89	2.31	3.01	−3.65
	(−0.83)	(−0.69)	(2.11)	(4.52)	(3.24)	(−3.72)

Table B4: **CDS trading and DES premiums**

This table reports average annualized excess returns and abnormal returns for DES stock and bond portfolios for the subsample of firms with or without CDS trading. In Panel A, we form stock quintile portfolios based on DES of the previous month for each subsample and then estimate the stock alphas from CAPM, Fama and French (1992) three-factor model (FF3), Carhart four-factor model (C4), Fama and French (2015) five-factor model (FF5), Stambaugh and Yuan (2017) mispricing factor model (M4), and Hou, Xue, and Zhang (2015) q-factor model (HXZ). In Panel B, we form bond quintile portfolios based on the bond-level DES of the previous month for each subsample and then estimate the one-factor bond alphas, α^{mkt}, by regressing excess bond returns on an intercept and the market bond returns (proxied by the Merrill Lynch Index) and estimate the four-factor bond alphas, α^{4F}, by regressing the excess bond returns on an intercept and four bond factors proposed by Bai et al. (2019). We report the results using the value-weighted (VW) scheme to save space. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is from January 2002 to December 2020, except for the bond four-factor model tests, where the sample period is from July 2004 to December 2019 owing to the availability of the Bai et al. (2019) factors.

Panel A: Stock portfolios

	With CDS					
	L(ow)	2	3	4	H(igh)	L-H
mean	14.45	8.98	6.38	6.45	6.94	7.51
	(3.70)	(3.01)	(1.89)	(1.89)	(1.69)	(2.90)
α^{CAPM}	5.44	1.56	−0.90	−0.46	−1.82	7.27
	(2.60)	(1.36)	(−0.92)	(−0.30)	(−0.78)	(2.47)
α^{FF3}	6.05	1.45	−0.97	−0.48	−1.17	7.22
	(3.01)	(1.31)	(−1.05)	(−0.30)	(−0.61)	(2.38)
α^{C4}	6.71	1.31	−1.44	−0.58	−1.06	7.77
	(3.77)	(1.18)	(−1.61)	(−0.38)	(−0.54)	(2.74)
α^{FF5}	4.69	1.23	−2.25	−2.50	−1.96	6.65
	(3.07)	(1.08)	(−2.43)	(−1.58)	(−1.10)	(2.50)
α^{M4}	7.16	1.52	−1.88	0.32	1.14	6.02
	(2.58)	(1.38)	(−1.61)	(0.20)	(0.72)	(1.59)
α^{HXZ}	6.59	0.79	−0.95	0.54	1.35	5.24
	(2.65)	(0.59)	(−1.13)	(0.33)	(0.80)	(1.46)

Without CDS						
	L(ow)	2	3	4	H(igh)	L-H
mean	13.61	10.30	7.42	5.74	4.08	9.53
	(2.43)	(2.69)	(1.91)	(1.32)	(0.66)	(2.85)
α^{CAPM}	2.42	1.69	−0.77	−3.58	−6.96	9.38
	(1.16)	(1.21)	(−0.62)	(−2.24)	(−2.03)	(2.47)
α^{FF3}	3.49	1.19	−0.78	−3.47	−6.30	9.79
	(1.79)	(0.92)	(−0.65)	(−2.08)	(−1.87)	(2.55)
α^{C4}	4.11	1.10	−0.99	−3.45	−6.15	10.26
	(2.23)	(0.87)	(−0.88)	(−2.02)	(−1.79)	(2.85)
α^{FF5}	3.65	1.04	−2.48	−5.20	−6.63	10.28
	(1.85)	(0.84)	(−1.89)	(−3.01)	(−1.97)	(2.85)
α^{M4}	6.80	0.72	−1.64	−1.93	−4.60	11.40
	(3.09)	(0.59)	(−1.29)	(−1.03)	(−1.17)	(2.32)
α^{HXZ}	4.31	0.84	−1.62	−2.20	−5.13	9.44
	(2.01)	(0.49)	(−1.40)	(−1.07)	(−1.14)	(1.94)

Panel B: Bond portfolios

With CDS						
	L(ow)	2	3	4	H(igh)	L-H
mean	3.58	4.28	4.96	5.65	8.40	−4.82
	(2.40)	(3.12)	(3.86)	(4.31)	(4.47)	(−3.86)
α^{mkt}	−0.67	0.28	0.98	1.57	3.64	−4.31
	(−1.00)	(0.41)	(1.45)	(2.86)	(2.63)	(−2.62)
α^{4f}	−1.17	−0.27	0.58	1.20	2.92	−4.09
	(−1.89)	(−0.44)	(1.00)	(2.22)	(2.69)	(−2.67)

Without CDS						
	L(ow)	2	3	4	H(igh)	L-H
mean	3.41	4.24	5.34	5.42	7.81	−4.40
	(2.32)	(3.08)	(3.87)	(3.46)	(3.33)	(−2.88)
α^{mkt}	−0.57	0.02	1.44	1.15	2.87	−3.43
	(−0.52)	(0.03)	(2.39)	(1.80)	(2.08)	(−2.78)
α^{4f}	−0.79	0.30	1.02	0.17	0.94	−1.74
	(−0.92)	(0.74)	(1.57)	(0.21)	(0.98)	(−1.46)

Table B5: **Time to maturity and bond DES premiums**

This table reports the average annualized value-weighted excess returns and Bai et al. (2019) four-factor model abnormal returns of the debt-equity spread (DES) portfolios, conditional on time to maturity. Each month we sequentially sort bonds into 3-by-3 portfolios based on time to maturity and DES. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is from January 1980 to December 2020. All four-factor model tests start in July 2004 owing to the availability of the Bai et al. (2019) factors.

	L(ow)	M(id)	H(igh)	L-H	L(ow)	M(id)	H(igh)	L-H
Low	1.96	2.71	5.06	−3.09	0.06	0.86	2.04	−1.98
	(1.85)	(2.94)	(5.79)	(−4.80)	(0.12)	(2.15)	(3.70)	(−2.33)
Mid	3.22	3.73	6.41	−3.19	0.30	0.90	1.11	−0.81
	(2.34)	(2.86)	(4.86)	(−4.66)	(0.71)	(1.83)	(1.40)	(−0.82)
Hi	3.75	5.38	7.46	−3.70	−1.80	−0.05	1.09	−2.89
	(2.37)	(3.67)	(5.07)	(−4.28)	(−3.32)	(−0.06)	(0.98)	(−2.60)

Table B6: **Capital structure arbitrage strategies**

This table reports average annualized excess returns and abnormal returns for the capital structure arbitrage strategies. We form quintile portfolios based on the bond-level debt-equity spread (DES) of the previous month, and for each DES quintile, we compute the average return of a hedged position that buys the bond and short-sells the stock of the same firm using the estimated bond-level hedge ratio. We also estimate the alphas from the CAPM model with both stock market and bond market factors and a seven-factor model with three equity factors from Fama and French (1992) and four bond factors from Bai et al. (2019). The sample is from January 1980 to December 2020, except for the seven-factor model tests, where the sample period is from July 2004 to December 2019 because of the availability of the Bai et al. (2019) factors. We report the results using both the value-weighted (VW) scheme and the equal-weighted (EW) scheme. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12.

	VW Returns					
	L(ow)	2	3	4	H(igh)	H-L
mean	−0.21	2.03	3.63	4.49	7.35	7.56
	(−0.18)	(1.65)	(3.09)	(3.83)	(6.14)	(7.21)
α^{mkt}	−2.88	−1.56	−0.05	0.95	3.75	6.63
	(−4.15)	(−2.77)	(−0.09)	(2.01)	(5.31)	(5.88)
α^{7f}	−1.03	−0.20	0.95	1.31	2.74	3.77
	(−1.26)	(−0.51)	(1.99)	(2.42)	(2.47)	(2.73)

	EW Returns					
	L(ow)	2	3	4	H(igh)	H-L
mean	−0.61	1.77	3.51	4.55	8.22	8.83
	(−0.53)	(1.41)	(3.04)	(4.04)	(6.41)	(8.16)
α^{mkt}	−3.06	−1.66	−0.11	1.02	4.69	7.75
	(−4.85)	(−2.78)	(−0.24)	(2.46)	(6.29)	(6.81)
α^{7f}	−1.68	−0.29	0.65	1.54	3.10	4.78
	(−2.17)	(−0.70)	(1.51)	(2.72)	(3.34)	(3.68)

Table B7: **Alternative controls for corporate security issuance and cash holdings**
This table examines the relation between debt-equity spread (DES) and corporate financial policies using alternative control variables. Panel A reports results from panel regressions of quarterly net equity issuance, net debt issuance, debt-equity swap, and change in cash holdings on the DES, actual credit spread (CS^D), and market-to-book equity ratio (ME/BE) of the previous quarter. Panel B reports results from logistic regressions of equity issuance for debt retirement (equity-debt swap) and indicators of cash reduction for debt retirement on the same set of key independent variables. We include standard control variables of the previous quarter, namely, leverage, the logarithm of total assets, tangibility, cash reserve and dividend payout, as well as profitability and capital investments of the contemporaneous quarter. We control for firm and time fixed effects across all specifications for panel regressions in Panel A. We demean all the variables at the firm level and control for time fixed effect for logistic regressions in Panel B. The variable definitions are in Panel C of Table 1. We report t-statistics for the panel regressions and z-statistics for logistic regressions in parentheses, and adjust the t-statistics using standard errors clustered at the firm level. The sample is quarterly from 1980 to 2020.

Panel A. Panel regressions									
	Equity issuance			Debt issuance			Change in cash holdings		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
DES(t-1)		0.10	0.12		−0.10	−0.23		−0.12	−0.24
		(3.77)	(4.19)		(−1.70)	(−3.58)		(−2.06)	(−3.78)
CS^D(t-1)	−0.03		−0.09	0.39		0.49	0.35		0.46
	(−1.02)		(−2.40)	(5.67)		(6.27)	(4.65)		(5.30)
ME/BE(t-1)	0.03	0.04	0.03	−0.26	−0.27	−0.27	0.05	0.03	0.04
	(0.74)	(0.82)	(0.78)	(−3.95)	(−4.12)	(−4.01)	(0.55)	(0.40)	(0.51)
MktLev(t-1)	0.05	0.06	0.06	−0.18	−0.16	−0.19	−0.08	−0.07	−0.10
	(10.99)	(12.23)	(11.68)	(−14.43)	(−13.78)	(−13.82)	(−7.88)	(−7.02)	(−8.45)
log(BA)(t-1)	−0.01	−0.01	−0.01	−0.01	−0.02	−0.01	−0.03	−0.03	−0.03
	(−5.22)	(−5.25)	(−5.38)	(−5.46)	(−6.36)	(−5.23)	(−8.80)	(−9.31)	(−8.57)
Profitability(t)	−0.00	−0.00	−0.00	−0.01	−0.01	−0.01	0.00	0.00	0.00
	(−1.57)	(−1.60)	(−1.60)	(−2.92)	(−2.92)	(−2.89)	(1.16)	(1.19)	(1.18)
Tangibility(t-1)	0.00	0.00	0.00	0.03	0.03	0.03	−0.02	−0.02	−0.02
	(0.47)	(0.48)	(0.50)	(2.00)	(2.05)	(1.97)	(−1.05)	(−1.03)	(−1.08)
Cash(t-1)	−0.05	−0.05	−0.05	−0.12	−0.12	−0.13	−0.95	−0.94	−0.95
	(−4.82)	(−4.76)	(−4.61)	(−4.97)	(−4.83)	(−5.09)	(−15.53)	(−15.55)	(−15.46)
Dividend(t-1)	−0.16	−0.16	−0.16	0.54	0.52	0.55	0.09	0.08	0.10
	(−2.54)	(−2.57)	(−2.65)	(6.63)	(6.48)	(6.79)	(0.90)	(0.76)	(1.01)
Investments(t)	0.08	0.08	0.08	0.57	0.57	0.57	−0.15	−0.16	−0.15
	(4.82)	(4.90)	(4.86)	(15.49)	(15.34)	(15.46)	(−5.96)	(−6.10)	(−6.01)
N_obs	45884	45884	45884	45884	45884	45884	45884	45884	45884
Adj. R^2	0.19	0.19	0.19	0.08	0.08	0.09	0.10	0.10	0.10

Panel B. Logistic regressions						
	Equity-debt swap			Cash reduction for debt retirement		
	(1)	(2)	(3)	(1)	(2)	(3)
DES(t-1)		2.58	5.29		1.23	2.91
		(2.92)	(5.49)		(1.46)	(3.25)
$\mathrm{CS}^{\mathrm{D}}(t-1)$	−7.66		−9.75	−5.24		−6.37
	(−6.87)		(−8.27)	(−5.01)		(−5.77)
ME/BE(t-1)	0.05	0.05	0.05	−0.00	−0.00	−0.00
	(5.07)	(5.10)	(5.30)	(−0.38)	(−0.38)	(−0.26)
MktLev(t-1)	1.70	1.43	2.07	1.86	1.65	2.06
	(11.84)	(10.32)	(13.03)	(13.78)	(12.67)	(13.87)
log(BA)(t-1)	−0.03	−0.02	−0.03	0.14	0.14	0.14
	(−1.09)	(−0.73)	(−1.14)	(5.22)	(5.51)	(5.21)
Profitability(t)	0.20	0.20	0.20	0.07	0.07	0.07
	(3.80)	(3.80)	(3.72)	(1.46)	(1.46)	(1.42)
Tangibility(t-1)	−0.42	−0.40	−0.43	−0.46	−0.44	−0.46
	(−2.14)	(−2.06)	(−2.19)	(−2.50)	(−2.42)	(−2.52)
Cash(t-1)	−0.01	−0.19	0.12	7.37	7.23	7.44
	(−0.03)	(−0.71)	(0.45)	(29.50)	(29.20)	(29.65)
Dividend(t-1)	−6.31	−6.01	−6.63	−4.75	−4.57	−4.92
	(−4.79)	(−4.57)	(−5.01)	(−3.93)	(−3.78)	(−4.06)
Investments(t)	−4.14	−3.99	−4.13	−2.32	−2.22	−2.32
	(−11.43)	(−11.05)	(−11.41)	(−6.98)	(−6.70)	(−6.97)
N_obs	45991	45991	45991	45991	45991	45991
Pseudo R^2	0.01	0.01	0.01	0.03	0.03	0.03

Table B8: **Tangible and intangible investments**

This table reports results from panel regressions of quarterly net capital investments, and research and development (R&D) investments on the debt-equity spread (DES), actual credit spread (CS^D) and market-to-book equity ratio (ME/BE) of the previous quarter. We include standard control variables of the previous quarter, namely, market leverage, the logarithm of total assets, profitability, tangibility, cash reserve, and dividend as well as firm and time fixed effects in all specifications. The variable definitions are in Panel C of Table 1. The *t*-statistics reported in parentheses are based on standard errors clustered at the firm level. The sample is from 1980 to 2020.

	Capital investments			R&D investments		
	(1)	(2)	(3)	(1)	(2)	(3)
DES		−0.06	−0.04		−0.00	−0.00
		(−2.95)	(−1.84)		(−0.07)	(−0.19)
CS^D	−0.08		−0.06	0.00		0.00
	(−2.60)		(−1.79)	(0.29)		(0.33)
ME/BE	0.10	0.10	0.10	0.03	0.03	0.03
	(3.82)	(3.83)	(3.80)	(2.20)	(2.20)	(2.20)
MktLev	−0.08	−0.09	−0.08	−0.00	−0.00	−0.00
	(−14.47)	(−16.46)	(−14.30)	(−0.55)	(−0.51)	(−0.55)
log(BA)	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(−2.03)	(−1.71)	(−1.95)	(−3.32)	(−3.40)	(−3.30)
Profitability	0.09	0.10	0.09	0.02	0.02	0.02
	(3.80)	(3.89)	(3.79)	(2.63)	(2.60)	(2.62)
Tangibility	0.08	0.08	0.08	0.01	0.01	0.01
	(10.06)	(10.06)	(10.05)	(2.54)	(2.55)	(2.54)
Cash	0.00	−0.00	0.00	0.01	0.01	0.01
	(0.20)	(−0.00)	(0.12)	(1.38)	(1.39)	(1.37)
Dividend	−0.07	−0.06	−0.07	0.02	0.02	0.02
	(−1.80)	(−1.65)	(−1.74)	(1.02)	(1.01)	(1.02)
N_obs	45879	45879	45879	46071	46071	46071
Pseudo R^2	0.64	0.64	0.64	0.62	0.62	0.62

Table B9: **DES and insider trading**
This table reports alternative tests for insider sales using a sample that include routines. We report results from panel regressions of the quarterly insider sales fraction on the debt-equity spread (DES). We use two measures to proxy for insider selling activities, including the fraction of insider sales volume (the number of shares sold divided by the total number of shares traded each quarter) and the fraction of insider sales (the number of sales divided by the total number of trades each quarter) . We merge the quarterly insider trading measure with our DES measure, which is the available in the previous quarter. We follow Guay et al. (2021) and include standard control variables of the previous quarter, namely, the logarithm of total assets, profitability, book leverage, and market-to-book equity ratio (ME/BE), as well as mispricing score (MispScore) (Stambaugh and Yuan, 2017). We include firm and time fixed effects in all specifications. The variable definitions are in Panel C of Table 1. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. The sample is from 1986 to 2019, except for Specification (4), where the sample ends in 2016 owing to the data availability of MispScore.

	Fraction of insider sales volume			Fraction of insider sales		
	(1)	(2)	(3)	(1)	(2)	(3)
DES	2.16	2.03	1.55	2.15	2.03	1.55
	(4.57)	(4.28)	(2.85)	(4.54)	(4.27)	(2.82)
CS^D	−4.41	−4.21	−3.84	−4.35	−4.15	−3.74
	(−7.68)	(−7.22)	(−5.94)	(−7.25)	(−6.85)	(−5.65)
ME/BE		0.01	0.01		0.01	0.01
		(2.49)	(1.39)		(2.40)	(1.27)
log(BA)	−0.04	−0.03	−0.05	−0.04	−0.03	−0.05
	(−2.34)	(−1.72)	(−2.92)	(−2.42)	(−1.82)	(−3.00)
Profitability	0.01	0.01	0.02	0.01	0.01	0.02
	(0.36)	(0.33)	(0.63)	(0.31)	(0.29)	(0.62)
Lev	−0.03	−0.08	−0.07	−0.03	−0.08	−0.07
	(−0.39)	(−1.10)	(−0.91)	(−0.40)	(−1.09)	(−0.90)
MispScore			−0.20			−0.20
			(−3.73)			(−3.73)
N_obs	14877	14877	12536	14877	14877	12536
Adj. R^2	0.38	0.38	0.35	0.38	0.38	0.35