The Debt-Equity Spread*

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Abstract

We propose the debt-equity spread (DES), the difference between the actual and equity-implied credit spreads, as a measure of the valuation gap between debt and equity at the firm and bond level. DES strongly predicts stock and bond returns in opposite directions. A strategy that takes a long position in firms with low DES (indicating that stocks are cheap relative to bonds) and a short position in those with high DES generates an average stock return of 7.72% and bond return of –4.97% per annum. The return predictability is consistently significant over subsamples and is stronger among smaller, less liquid, and more difficult-to-short stocks and bonds. In addition, firms with higher DES tend to have more negative revisions in long-term growth forecasts, issue equity and retire debt more aggressively, and their insiders are more likely to sell their stocks. Together, these findings support DES being a measure of relative mispricing between debt and equity.

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

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1 Introduction

In standard asset pricing models, a firm's equity and debt should be priced consistently under the principle of no arbitrage, as both are contingent claims on the same underlying asset (see the seminal work of Merton, 1974). However, due to market segmentation and other frictions, the equity and debt of the same firm could be subject to misvaluation at different degrees, resulting in a valuation gap. Moreover, if the relative mispricing is persistent, it could have important implications for investors and firm managers.

In this study, we propose a simple measure of the firm-level valuation gap between debt and equity and study its implications for stock and bond returns, as well as corporate decisions. Our measure, the debt-equity spread (DES), is the difference between two credit spreads:

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

where the equity-implied credit spread is computed using an industry standard CreditGrades model which we have extended to take into account the heterogeneity in firm payouts. When a firm's equity is valued high relative to its debt, the equity-implied credit spread tends to be low relative to the actual bond spread, giving rise to a higher DES. In contrast, low equity valuation relative to debt results in a low DES. The DES measure thus integrates the information from both bond and equity markets.

Converting equity value to a credit spread facilitates the comparison between equity and debt valuations. It is similar to comparing option valuations at different maturities or strikes by converting option price into an implied volatility, and like implied volatility, this conversion is model-dependent. While a more sophisticated structural model could potentially reduce the concern for model misspecification, we choose the CreditGrades model because of its simplicity (similar to the common choice of Black-Scholes implied volatility) and wide application in the industry.[1] The standard CreditGrades model is based on Black and Cox (1976) and adds an additional feature of uncertain default boundary to address the difficulties of diffusion-based models in pricing shorter-maturity debt. The key inputs include market value of equity, financial leverage, stock return volatility, and bond-level information (e.g., coupon schedule and maturity). An added input in our extended CreditGrades model is the expected firm payout ratio.[2]

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

[2] In order to obtain an approximate solution, the original CreditGrades model restricts the firm value to have zero expected growth under the risk-neutral measure. We also derive an exact close-form solution for our extended model.

We study the predictive power of DES for the cross section of stock and bond returns in the US market from January 1980 to December 2020. While DES negatively predicts the cross section of stock returns, it positively predicts the cross section of corporate bond returns. When sorting stocks into quintiles based on firm-level DES, we find that stocks in the high-DES quintile have an average value-weighted return of 4.57% per year, compared to 12.29% for those in the low-DES quintile. The average return spread between them is 7.72% per year, with a t-statistic of 4.29 (the average equal-weighted annual excess return is 7.93%, with a t-statistic of 4.33). At the same time, bonds in the high-DES quintile outperform those in the low-DES quintile by 4.97% per year (with a t-statistic of 5.41) for the value-weighted portfolios and 6.35% per year (with a t-statistic of 6.37) for the equal-weighted portfolios. These results are robust to various controls of standard factors as well as firm, equity, and bond characteristics.

The opposite directions in the stock and bond return predictability of DES is consistent with it capturing the relative mispricing between equity and debt. It presents a challenge for a set of standard risk-based explanations which feature risk factors that the stock and bonds of the same firm are exposed to in the same direction. We test several possible risk-based explanations that can plausibly generate risk exposures for stocks and bonds in opposite directions, including 1) systematic volatility shocks (both realized and implied), 2) shocks to a common component of idiosyncratic volatility (Herskovic et al., 2016), 3) aggregate jump risk, 4) investment-specific technology shocks (Kogan and Papanikolaou, 2014), and 5) variation in government bond yield. The time series regression tests show that the DES bond and stock return spreads are unlikely to be driven by these risk factors.

To further distinguish between the mispricing vs. risk-based explanation, we examine three additional results.

First, we examine the relation between DES and analysts' long-term earnings growth forecasts, which likely have a bigger impact on the pricing of stocks than bonds. Contemporaneously, high-DES stocks tend to have higher long-term growth than low-DES stocks. Furthermore, DES negatively predicts changes in earnings growth forecasts from year 2 through year 5, indicating that analysts are more likely to be disappointed by high-DES stocks and make negative forecast revisions in the subsequent years.

Second, mispricing is likely to be more pronounced and persistent among securities that face more severe limits to arbitrage. For this reason, we examine the relation between DES return predictability and a variety of proxies for limits to arbitrage. DES stock return spreads are substantially stronger among stocks that (1) have lower market capitalization, (2) are less liquid (based on dollar volume and the measure of Amihud, 2002), (3) have lower dollar trading volume, (4) are more costly to short (based on equity lending fee), (5) are more risky to short (based on days to cover), and (6) have wider analyst forecast dispersion. Similarly, DES bond return spreads are stronger among bonds with smaller bond size, lower dollar volume, lower number of trading days, larger Amihud illiquidity, and larger gamma (Bao et al., 2011). Interestingly, we also find that the predictability of DES for stock returns is stronger among firms that have more liquid bonds. This is consistent with bond prices of these firms being less affected by the illiquidity premium and better captured by our structural model, which in turn makes the DES measure more informative about stock misvaluation (rather than being contaminated by model misspecification).

Third, if DES captures relative mispricing, corporations and their insiders are likely to take advantage of the arbitrage opportunities. Consistent with high DES being associated with relatively over-priced equity and under-priced debt, we find that high DES non-financial firms simultaneously issue more equity and retire more debt. Our result is consistent with the finding of Ma (2019) that net equity repurchases and net debt issuance both increase when expected excess returns on debt are particularly low, or when expected excess returns on equity are relatively high. Our DES measure has additional predictive power beyond the stock- and bond-level measures used by Ma (2019), likely because it provides a direct comparison between debt and equity valuations. Furthermore, we find that top executives of high DES firms are more likely to sell their stocks in subsequent months than those of low DES firms. These behaviors of corporate managers and insiders provide additional validations for our measure of valuation gap between equity and debt markets.

Taken together, while it is difficult to completely rule out risk-based explanations, our results suggest DES is more likely to be a measure of relative mispricing. Compared to other mispricing measures in the literature, DES has its unique features. First, DES is economically driven and exploits the difference in the valuation between equity and bond markets through the lens of a structural model. Therefore, it complements measures of valuation ratios, which rely on accounting variables such as book equity or earnings as the benchmark, or mispricing score by Stambaugh et al. (2012), which is based on several well-documented anomalies in the stock market. Second, to the extent that equity valuation is more sensitive to firms' growth options and intangible assets while bond valuation is more sensitive to tangible assets in place and downside risks, DES could capture "value" in a way that is more robust to the critiques by Arnott et al. (2021) and Eisfeldt et al. (2020).

Related literature Our study contributes to the literature that examines the integration between the equity and credit markets. Schaefer and Strebulaev (2008) demonstrate that hedge ratios from the simple credit risk model of Merton (1974) are helpful in explaining the co-movement between equity and bond returns, because the hedge ratio is not "contaminated" by bond liquidity risk. Extending this line of research, Choi and Kim (2018) 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) highlight the importance of limits to arbitrage in understanding the disintegration between these two markets. Culp et al. (2018) construct option-based credit spreads from S&P500 (SPX) index put options and find a good deal of integration between corporate bond and option markets at the aggregate level.[3]

Trading strategies that exploit relative mispricing between debt and equity are often referred to as capital structure arbitrage, which had its hay days in the early 2000s. Such strategies are most commonly implemented through equity and credit default swaps (CDS). Yu (2006) is among the first to systematically examine the profitability of such strategies. Using the CreditGrades model and the 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 firm level, while the portfolio level tests produce statistically insignificant excess returns due to 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 both in the time series and cross section. By taking a long-short position in DES quintiles, we find the capital structure arbitrage can achieve a better risk-return tradeoff, which is discussed in more detail in Section 3.5. In addition, we separately examine the predictability of stock and bond returns, as well as other corporate decisions.

Our paper contributes to the literature on mispricing and return predictions. Earlier studies such as De Bondt and Thaler (1985), Lakonishok et al. (1994), and La Porta (1996) find that investors may become excessively pessimistic about future earnings growth after a series of bad earnings or other negative news, and these out-of-favor stocks are therefore undervalued and their prices rises in subsequent periods. These studies use this extrapolative bias to explain the long-term contrarian effect and the value premium. Baker and Wurgler (2006) study how investor sentiment affects cross-sectional stock returns. Stambaugh et al.

[3]Related, Collin-Dufresn et al. (2001) examine the exploratory power of equity market variables on credit spreads, while Koijen et al. (2017) show that bond factors are priced in equity returns. Other studies examine the relation between equity and credit default swap (CDS) markets. Longstaff et al. (2005) examine the lead-lag relation between equity, bond and CDS markets and find that the former two markets help to predict corporate yield spread changes. Duarte et al. (2007) study the risk and return of popular fixed-income arbitrage strategies. Friewald et al. (2014) estimate the distress risk premium implied by CDS markets and find a positive relation between the distress risk premium and stock returns. By constructing optimal Sharpe ratio portfolios that are consistent with no-arbitrage and trading frictions, Sandulescu (2021) documents a non-trivial but not perfect integration between U.S. stock and corporate bond markets.

(2012) combine market-wide sentiment with short-sale impediments (Miller, 1977) and predict that overpricing in asset prices should be more prevalent than underpricing, which can be used to understand the behaviors of a broad set of anomalies in cross-sectional stock returns. Complementary to Stambaugh et al. (2012) which extract equity overpricing information from existing stock anomalies, our work proposes a mispricing measure that connects equity and debt markets and documents its opposite signs in predicting equity and bond returns.[4]

Our work also adds to the extant literature on corporate security issues and investments. Dong et al. (2012) adopt the discounted cash flows method to examine whether equity issuance is driven by overvalued equity. Using the actual credit spread, term spread, and stock returns separately from the equity and bond markets, Ma (2019) documents that non-financial firms arbitrage across their own equity and bond. Our result shows a valuation gap measure that integrates information from both markets has additional predictive power for firms' cross-market arbitraging behaviors.

The paper proceeds as follows. In Section 2, we describe the construction of DES. In Section 3, we study the implications of DES for the 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 examine the relation between DES and 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 relatively transparent and easy to implement. Different from the models in Cremers et al. (2008), Huang and Huang (2012), and Bai et al. (2020), which rely on jumps to raise credit spreads, the standard CreditGrades model introduces uncertainty about the default boundary.

Under the risk-neutral measure, the dynamics of the asset value, V_t, of a solvent firm

[4]More broadly, this paper is related to the large and fast-growing literature on behavioral finance and asset pricing. See Barberis and Thaler (2003), Hirshleifer (2001) and Barberis (2018) for excellent reviews on this area.

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. While the standard CreditGrades model assumes a zero drift under the risk-neutral measure, i.e., $r = \delta$, we allow for cross-sectional heterogeneity in the payout ratio δ, which further increases the average credit spread due to 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

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

and Z is independent of W_t. Thus, $\mathbf{E}(L) = \overline{L}$ and $\mathbf{var}(L) = \lambda^2$. Notice that the presence of stochastic default boundary makes the timing of default not predictable. Intuitively, at any asset value, there is a finite probability that default can occur instantaneously when Z is sufficiently large. This is similar in spirit to Duffie and Lando (2001), who introduce uncertainty about the value of firm assets due to 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

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

Since

$$\mathbb{P}\{Y_s > y, \forall s < t\} = \Phi\left(\frac{at-y}{\sigma\sqrt{t}}\right) - e^{2ay/\sigma^2}\Phi\left(\frac{at+y}{\sigma\sqrt{t}}\right), \tag{4}$$

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

$$q(t|z) = \Phi\left(C \cdot A(t) - \frac{y}{A(t)}\right) - e^{2Cy}\Phi\left(C \cdot A(t) + \frac{y}{A(t)}\right), \tag{5}$$

[5] Our results are robust to different model specification when applying the Black-Cox model in the online appendix B.2.

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

$$C = \frac{r-\delta}{\sigma^2} - \frac{1}{2}, \tag{6a}$$

$$A(t) = \sigma\sqrt{t}, \tag{6b}$$

$$y = \log\left(\frac{\overline{L}D}{V_0}\right) - \frac{\lambda^2}{2} + \lambda z. \tag{6c}$$

Next,

$$\begin{aligned} q'(t|z) = {} & \phi\left(C \cdot A(t) - \frac{y}{A(t)}\right)\left(C \cdot A'(t) + \frac{yA'(t)}{A^2(t)}\right) \\ & - e^{2Cy}\phi\left(C \cdot A(t) + \frac{y}{A(t)}\right)\left(C \cdot A'(t) - \frac{yA'(t)}{A^2(t)}\right), \end{aligned} \tag{7}$$

where $A'(t) = \frac{\sigma^2}{2A(t)}$.

The unconditional survival probability $q(t)$ is then given by

$$q(t) = \int_{-\infty}^{\overline{Z}} q(t|z) d\Phi(z), \tag{8}$$

with

$$\overline{Z} = \frac{\lambda}{2} - \frac{1}{\lambda}\log\left(\frac{\overline{L}D}{V_0}\right). \tag{9}$$

Eq. (8) can be further expressed in terms of the cumulative distribution functions of bivariate normal distributions.

Accordingly, the price of a T-period coupon bond with annual coupon rate c and face value \$1 is:

$$D_0(T) = E_0^Q\left[\int_0^T e^{-\int_0^s r_u du} c 1_{\{\tau>s\}} ds + e^{-\int_0^T r_u du} 1_{\{\tau>T\}} + \int_0^T e^{-\int_0^s r_u du} L\, 1_{\{\tau=s\}} ds\right]. \tag{10}$$

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

$$D_0(T) = \sum_s P_0(s)q(s)c + P_0(T)q(T) - \int_0^T P_0(s)q'(s)\overline{L}ds, \tag{11}$$

where $P_0(s)$ is the price of a risk-less zero-coupon bond with maturity s at time 0.

2.2 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.

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 U.S. corporate bond markets since 2005. Follow 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.

We set the current date as time 0, and following the standard CreditGrades model, we approximate the market value of the firm V_0 as:

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

where S_0 is the equity value from daily CRSP data set, and D is the total liability (data item LT) from Compustat. When calculating S_0, we match the date of stock price with that for 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 (equation (6c)) and the survival probability (equation (8)). All else being equal, a higher equity value increases 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 the 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 $R_0 = S_0/(S_0 + D)$, 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 deleverging procedure that gives rise to unreasonably small asset volatilities for highly distressed and leveraged firms.

To calculate the bond value in equation (11), we interpolate, in an interval of six month, 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 the dividend, interest expenses, and stock repurchases, divided by the sum of market value of equity and debt each quarter. Dividend payment is the indicated annual dividend (DVI) from Compustat, multiplied by the number of shares. The indicated annual dividend is updated on a daily basis and is adjusted for stock splits, etc. Net stock repurchases are the total repurchase of common and preferred stock, and interest payments to debt holders are calculated as total interest payments 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.

2.3 The debt-equity spread

With the above inputs, we solve for the theoretical bond price in equation (11) and convert it to the equity-implied credit spread $\mathrm{CS^E}$. 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 flows as the underlying bond. Then, we obtain the difference between the actual spread $\mathrm{CS^D}$ and the equity-implied spread $\mathrm{CS^E}$ for each bond, each month, as our valuation gap measure:

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

Since credit spreads and equity valuation are negatively related in the CreditGrades model, DES potentially measures the degree of equity overpricing relative to bond value. When the actual credit spread ($\mathrm{CS^D}$) is high relative to the equity-implied credit spread ($\mathrm{CS^E}$), equity investors can be more optimistic about the firm's fundamentals than the bond investors, and stocks are overpriced. On the other hand, when $\mathrm{CS^D}$ is less than $\mathrm{CS^E}$, the stock price can be relatively undervalued.

We measure firm-level credit spreads (both actual and implied) and DES as the bond market value-weighted average of credit spreads and DES across all bonds within a firm. 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.

Panel A of Figure 1 plots monthly equity-implied credit spreads of five quintile portfolios, sorted by actual credit spreads. Portfolio credit spreads are calculated as the equity market value weighted average credit spreads across all firms within a portfolio. Panel A shows that the extended CreditGrades model generates large variations in the credit spreads. The 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 1800 basis points. Panel B illustrates the histogram of the monthly portfolio DES. For the actual credit spread quintiles, DES ranges from less than -400 basis points to 800 basis points. Furthermore, DES is in general normally distributed with a mean of 25.17 basis points, and slightly skewed to the right. In an untabulated analysis, we find the match between actual and equity-implied credit spreads is noisier at the bond level, with an average bond-level DES about 70 bps, implying that model-implied credit spreads undershoot those in the data. This is consistent with the literature on the credit spread puzzle and the fact that a part of the actual spreads are due to secondary-market illiquidity that is absent in the CreditGrades model.[6]

[Insert Figure 1 here]

Figure 2 plots the time series of the distribution of firm-level DES, including its median, 25th and 75th percentiles. 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]

Overall, the results in this section indicate that our extended CreditGrades model does a reasonable job in matching the observed credit spreads.

[6]See Jones et al. (1984) and Huang and Huang (2012) for the "credit risk puzzle". While recent developments in the literature have introduced various ingredients into the simple model, such as time-varying volatility, the market risk premium, jumps, and countercyclical bankruptcy costs (Chen et al., 2009; Chen, 2010; Bhamra et al., 2010; Du et al., 2019), it is still under debate whether a simple model, like Black and Cox (1976), is able to account for the credit risk premium (Chen et al., 2009; Feldhütter and Schaefer, 2018; Bai et al., 2020). See Longstaff et al. (2005) and Chen et al. (2018) for the decomposition of credit spreads into default and liquidity components.

3 Asset pricing

In this section, we study the asset-pricing implications of DES. 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 regression in Section 3.3. In Section 3.4, we conduct several empirical tests to differentiate the mispricing interpretation from risk-based explanations. We link our results to the capital structure abitrage in Section 3.5.

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 are overlapped for the same bond, we use the one from NAIC because they are transaction-based. The detailed calculation can be found in 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 Panels A and B of Table 1.

[Insert Table 1 here]

3.2 DES portfolios

We start our analyses on 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 the summary statistics of the characteristics of these portfolios. Panel A examines the relation between DES and its input variables in the extended CreditGrades model. Due to 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. 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 is non-monotonic.

[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 top DES quintile tend to have smaller market capitalization, 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, Stambaugh and Yuan (2017) mispricing factor model, and Hou et al. (2015) q-factor model (HXZ), for the DES quintile portfolios. We report the results using both value-weighted (VW) scheme and equal-weighted (EW) scheme. Panel A shows stocks with high DES have an average VW return of 4.57% per year, lower than the 12.29% for stocks with 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 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 about firms' misvaluations from the two mispricing factors in Stambaugh and Yuan (2017).

As reported Panel A of Table 3, the results using the equally weighted portfolios are similar and quantitatively stronger than those of the 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 buys low-DES stocks and short-sells high-DES stocks. The value-weighted strategy produces relatively stable returns. Interestingly, the equally weighted portfolio generates similar performance as 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.[7]

[Insert Figure 3 here]

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 the equity market, 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 the standard factors. When we regress 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 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 $= -2.05$).[8] We observe quantitatively stronger results when we 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

[7]In the appendix, we explore the long-horizon stock return prediction of DES using buy-and-hold portfolios. We find that DES significantly predicts stock return 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.

[8]Note the sample period for the four-factor model test only starts in July 2004 due to the data availability of Bai et al. (2019) factors.

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.

3.2.3 Subsample analyses

We formally test the stability of 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 4 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 is 7.71% (8.51%) from January 2000 to December 2020. Moreover, the abnormal returns from the 4-factor Carhart model, α^{C4}, increase from the raw return spreads in both subsamples.

[Insert Table 4 here]

We find similarly stable return prediction 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 is -5.58% (-7.32%) from January 2000 to December 2020. After controlling the bond market factor, the abnormal bond returns, α^{mkt}, remain economically and statistically significant.

3.3 Fama-MacBeth regressions

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

We present results for stock returns in Panel A of Table 5, 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), and asset growth (AG), and asset tangibility (Tangibility).

[Insert Table 5 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 the mispricing score (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. 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 Panel B, we report the results from monthly Fama-MacBeth bond return predictive regressions controlling for both firm and bond characteristics. 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 5. The positive coefficient on market leverage reflects the greater default risk associated with a higher leverage. When bond characteristics, including logarithm of bond size (logBondSize), amount outstanding (Amount), bond age (Age), coupon rate (Coupon), and bond maturity (Maturity), are also controlled in Specification 5, 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.

In Specifications 7 and 8 of Panel B, we also control for mispricing score (MispScore) from Stambaugh et al. (2012). While DES remains a strong, positive return predictor, we find the coefficient on MispScore is negative but statistically insignificant. Along with the finding from the stock return prediction in Panel A, this result highlights an important difference between DES and MispScore. The negative coefficients of MispScore in both stock and bond return predictions is consistent with MispScore being a mispricing measure of the underlying asset, that is, absolute mispricing. In contrast, the opposite signs of the DES coefficients from stock and bond predictions suggest that DES is likely to capture the *relative* mispricing between equity and debt of the same underlying asset. The opposite signs are also inconsistent with rational explanations based on asset risk. If DES measures asset risk exposure, the stock and bond risk premiums should increase or decrease with DES simultaneously, because both securities are contingent claims on the same underlying assets.

CreditGrades model inputs: One may wonder if the return predictive power of DES is driven by the inputs of the extended CreditGrades model. We address this question in Table 6. In Panel A, we study how the model inputs predict the cross-sectional stock return 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 Fama-MacBeth regression between DES and these model inputs in Specification (5), DES remains a strong return predictor whose coefficient barely changes from the univariate regression in Specification (1).

[Insert Table 6 here]

Furthermore, we horse race DES with 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} and CS^{E} has a significant coefficient in the Fama-MacBeth regressions. In the bivariate regressions in Specifications (7) and (9), only the coefficient of DES remains statistically significant.

In Panel B, we compare the performance of DES and CreditGrades model inputs and implied and actual credit spreads in predicting bond returns. Besides the firm characteristics from Panel A, we also include bond maturity and dummy variable for callable bonds in the Fama-MacBeth regressions. Again, we find the coefficient of DES remains statistically significant after controlling for these model inputs and credit spreads.

Taken together, these results suggest the return predictive power of DES does not come from the CreditGrades model inputs, implied credit spreads, or actual credit spreads alone. Instead, it is the difference between the actual and implied credit spreads, or the valuation gap between equity and debt markets, that contains the information about future stock and bond returns in the cross section.

3.4 Risk or behavioral bias?

In this section, we provide empirical evidences for economic interpretations of the DES return predictive power.

3.4.1 Firm dynamics

We start by examining the dynamics of firms with different DES. Figure 4 plots the average DES, equity-implied credit spread (CS^{E}), actual credit spread (CS^{D}), asset volatility (Avol), financial leverage (Lev), payout ratio (Payout), gross profitability (GP), failure probability (FP), and stock returns (Ret) for firms in the low- and high-DES quintiles, five years before and five years after the portfolio rebalancing (i.e., event year 0). The figure shows that, although the spread in DES between these two portfolios is the largest around year 0 (by construction), the difference is highly persistent. Even five years after (and before) portfolio rebalancing, there is a sizable spread in DES (about 200 bps) between these two portfolios.

[Insert Figure 4 here]

The second and third columns in the first row show that, before portfolio formation, both high- and low-DES firms experience increases in CS^{D}, indicating that bond investors consider these stocks getting riskier. However, equity investors in these two groups of stocks think differently. While the equity-implied credit spread also increases for low-DES firms, the investors in the high-DES stocks disagree with the bond investors and the equity-implied credit spread actually falls before year 0.

The remaining panels of Figure 4 provide additional insights on this divergence. In the years before portfolio formation, high-DES firms have high gross profitability, good stock performance, and decreasing payout rate. In contrast, low-DES firms suffer from low profitability and stock returns. Their payout rate, failure probability, and financial leverage all increase substantially, and therefore, both equity and bond investors perceive high credit risk in these stocks.

The difference in firm dynamics can be consistent with both risk exposures and behavioral biases. As we have discussed earlier, investors can overreact to the past stock and accounting performances, giving rise to an overvaluation of high-DES stocks and undervaluation of low-DES stocks relative to their bond prices. Alternatively, high DES firms have high valuation ratios and have more growth options than low DES firms. To the extent that growth options have different risk premiums than assets-in-place, the valuation gap may arise from model misspecifications and correlate with firms' systematic risk. The rest of this section is aimed at differentiating these two channels.

3.4.2 Analyst long-term earnings forecasts

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 think like them, are too optimistic about stocks with rapidly growing earnings and too pessimistic about stocks with deteriorating earnings. In this subsection, we examine the relation between DES and analyst LTG. If DES captures equity overpricing, we expect high-DES stocks to have high contemporaneous LTG relative to stocks with low DES. Furthermore, these high forecasts of earnings growth would gradually be corrected by disappointment in subsequent years.

We obtain the LTG data from the IBES summary unadjusted file. Table 7 confirms our conjecture. Panel A summarizes the average 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 smaller than the 12.73% per year seen for stocks with high DES. This positive correlation between LTG and contemporaneous DES suggests that high-DES stocks may be more overvalued by analysts than stocks with low DES.

[Insert Table 7 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 our DES measure. We find the estimated coefficient of DES negative but insignificant, in predicting the revision in the next 12 months . However, from 24 months ahead, the coefficient of DES becomes statistically significant. Its magnitude increases with the horizon, with the estimated coefficient rising from -0.15 for the 24-month revision to -0.32 for the 60-month revision. These results indicate a strong mean reversion of the forecasted earnings growth, lending support to a mispricing interpretation of DES.

3.4.3 Limits to arbitrage

In the section, we 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 with higher limits to arbitrage (Shleifer and Vishny, 1997). We perform sequential double sorts to test this prediction. That is, we first sort stocks and bonds into terciles on proxies of limits to arbitrage and then within each tercile of the limits to arbitrage proxy, sort into terciles on DES.

[Insert Table 8 here]

Table 8 reports the DES portfolio returns for each tercile based on the limits to arbitrage measures. We consider six proxies for stock liquidity: 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 small, illiquid stocks with lower dollar trading volume, more days to cover, higher equity lending fees, and greater 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 conditions remain largely the same, after controlling for Carhart four factors.

When it comes to bond markets, we choose five different proxies, namely, bond size, Amihud illiquidity, dollar volume, gamma (Bao et al., 2011), and the number of trading days within each month. Except for the bond size, all the rest four measures are constructed using the transaction data from TRACE from 2002 to 2020. As shown in Table 9 and similar to that in stocks, the DES premium in bonds is substantially larger among small bonds, with a high level of Amihund illiquidity, low turnover, high bond gamma, and low number of trading days. Among all the five measures, bond size demonstrates the largest difference in the DES premium between high and low terciles. That is, the DES premium is -2.13% per year for big bonds, in contrast to -7.03% for small bonds.

[Insert Table 9 here]

In Table 10, we examine the effect of bond illiquidity on DES stock premiums. Studies including Dick-Nielsen (2009), Bao et al. (2011), Friewald et al. (2014), and Lin et al. (2011) document an important contribution of bond illiquidity to the observed credit spread. Since our extended CreditGrades model abstracts from bond illiquidity, we expect a negative correlation between stock DES premium and bond illiquidity, because more liquid bonds are better captured by the extended CreditGrades model, which in turn makes DES more informative about stock misvaluation. Indeed, the results in Table 10 show that the stock DES premium is stronger in firms with lower bond Amihud illiquidity, higher bond dollar volume, and greater number of tradedays of bonds.

[Insert Table 10 here]

Taken together, the results on limits to arbitrage lend further support to the mispricing interpretation of the DES premium.

3.4.4 Risk factor exposures

The asset pricing test results in Section 3.2 show that the DES stock and bond portfolio returns cannot be explained by the standard factor models in the literature. To the extent that some of these factor models such as CAPM, Fama and French 3-factor model, and Hou, Xue, and Zhang (2015) 4-factor model capture systematic risks, the asset pricing test results suggest that the return prediction of DES is beyond these risk exposures. However, it is still possible that DES predicts returns due to its exposure to other macroeconomic risk factors not captured by these factor models. In this section, we consider two such possibilities.

One possible risk channel is through volatility shocks. Due to the nonlinear features of equity and debt in structural models (e.g., Merton (1974)), an increase in asset volatility can raise stock price but lowers the corresponding bond price. Furthermore, as shown in Figure 4, high DES firms tend to have high valuation ratios, so their stocks, which derives much of their values from growth options, may benefit more from an increase in asset volatility. In contrast, low DES firms suffer from past low profitability and stock returns and have higher financial leverage. An increase in asset volatility lowers their bond values more than bonds of high DES firms. 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 volatility exposures of stocks and bonds across DES quintiles can possibly explain a negative DES stock return spread and a positive DES bond return spread.

We test this risk channel and report the results in Panel A for stocks and Panel B for bonds in Table 11. 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), 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 CBOE VIX (dVIX). A caveat for the last two measures is that they may also capture the quantity of systematic risk that affects the discount rate. For each volatility measure, we run time series regressions of the DES portfolio return on the market factor and the volatility shock measure. 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, and the stock return betas tend to be more negative for high DES firms than low DES firms. However, this would require a positive volatility risk premium to explain the average returns across these DES quintiles, which is in contrast to the findings of a negative risk premium for dCIV in Herskovic et al. (2016) and aggregate volatility risk in Ang et al. (2006). 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 non-monotonic across the DES quintiles. Therefore, the volatility exposures are unlikely to explain the difference in the stock and bond DES return spreads.

[Insert Table 11 here]

Another related possibility is the exposure to jump risk. 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 exposures because our model abstracts from jump process and can be misspecified. 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. Panel A, Table 11 shows that there is no significant difference in jump risk exposure between the high and low DES stocks. In Panel B, the relation between jump beta and DES is again non-monotonic across DES bond portfolios. In the online appendix, we double sort bonds into 3-by-3 portfolios based on their time-to-maturity and DES. Bai et al. (2020) document that short-maturity bonds are more exposed to the 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 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, these evidences combined suggest that jump risk cannot be a major explanation for the DES premiums

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 higher exposures to the investment-specific technology shocks than 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 than growth stocks. Because of the nature of equity and bond contracts, stocks can be more informative about growth options than bonds, so the second possibility is that the difference in their exposures to the investment shocks can explain the cross-sectional stock and bond returns based on DES sorts. The next two specifications of Table 11 again do not support this interpretation. When we use the investment-minus-consumption (IMC) portfolio return and the negative change in the price of equipment relative to nondurable consumption goods (Ishock) as the investment shock measures, we find the investment shock betas are weak and non-monotonic across stock and bond DES quintiles.

Lastly, we examine the exposures of DES portfolios on the change in the 10-year government bond yield. If these quintiles have different durations and exposures to the government bond yield change, they may have different risk premiums. The last row of each panel in Table 11 shows that there is not evident, monotonic pattern in the exposure to the yield change across these portfolios. Taken together, our results in this section do not find empirical supports for a risk-based explanation of the stock and bond returns across DES portfolios.

3.5 Relation to capital structure arbitrage

The previous subsections uncover a robust predictive power of DES on the cross-sectional stock and bond returns separately. The opposite signs on the stock and bond return predictions suggest that investors could combine these two asset classes to achieve an even better risk-return tradeoff, an idea that is 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 and make risk-free profits. Because the estimated hedge ratio depends on a specific credit risk model, it potentially suffers from model misspecifications and measurement errors, therefore having residual exposures 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 due to 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.[9]

To implement the capital structure arbitrage strategy, we short-sell $\$\eta$ of stock for each dollar of bond purchased. The return from this strategy, $r^H = r^D - \eta r^S$, is expected to have zero exposure to the asset risk, where r^D and r^S is bond and stock return, respectively. In the context of our analyses, if r^H reflects the correction of mispricing between the stock and bond markets, and if DES captures the strength of relative mispricing, we expect average r^H increases 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 12 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 7-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.[10] Consistent with our conjecture, the average hedged return increases strongly with

[9] 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 our 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.

[10] The average hedged returns are positive for all portfolios except the low DES quintile. This is likely because r^H does not completely hedge out all asset risks due to model misspecifications or measurement errors described above, and the positive average returns may reflect the premiums associated with the remaining

DES. The average hedged return is -0.21% per year for low DES quintile, as compared to 7.35% per year for the high DES quintile. Their difference is more than 7 standard deviations from zero.

[Insert Table 12 here]

The larger t-statistic in the H-L portfolio than those of the individual DES quintiles is worth noting and is due to 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 high and low DES hedged quintiles could reduce the remaining systematic risk exposures and achieve an even better risk-return tradeoff.

The pattern is similar when we control for equity and bond factors and when we use equal-weighted portfolios (Panel B, Table 12). In Figure 5, we plot the cumulative returns of the long-short hedged position for both value-weighted and equal-weighted portfolios. Compared with the same plots for equity-alone and bond-alone DES strategies, the hedged position features much lower volatility an better performances. $1 invested in this hedged portfolio at the beginning of the sample period can be turned into around $20 in the value-weighted strategy and more than $30 in the equal-weighted strategy.

[Insert Figure 5 here]

Taken together, our findings on the stock and bond return predictions of DES can be used to improve the performance of capital structure arbitrage strategy.

4 Corporate decisions and insider trading

We have demonstrated the implications of our valuation gap measure, DES, for investors in the equity and bond markets. 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 actions, including corporate security issuance and insider trading.

Unlike outside investors, a firm's management team usually possesses private information and is better at assessing the true values of their company's stocks and bonds. Thus, if DES

systematic risk exposures. Indeed, we find that the betas of all DES quintiles to the bond market factor are very close to one (untabulated), and after controlling for the bond and equity factors, the average abnormal hedged return across DES quintiles is much closer to zero.

truly measures the valuation gap between debt and equity, we expect the management to take advantage of this gap by issuing securities and, perhaps, trading stocks in their compensation packages.

4.1 Corporate security issuance

Firms time the market when issuing securities. They tend to 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 (Ritter, 1991; Baker and Wurgler, 2000; Hong et al., 2008; Dong et al., 2012). Baker and Wurgler (2002) show that a firm's capital structure is mainly attributed to "equity market timing". However, there is scarce evidence of firms' timing debt markets or jointly timing both debt and equity markets. One exception is Ma (2019), who documents that non-financial firms arbitrage by simultaneously issuing and repurchasing across equity and bond markets. She uses CDS and bond returns to proxy for the mispricing of corporate debt, maybe because there is no widely agreed measure of debt mispricing in the current literature. Therefore, our DES measure is particularly useful in studying cross-market arbitrages.

We examine the predictive power of DES for corporate securities issuance. We run panel and logistic regressions of quarterly corporate activities on lagged DES, and other mispricing variables, namely, actual credit spreads, market-to-book equity (ME/BE) ratio and mispricing score. We follow Ma (2019) and use actual credit spreads to proxy for the debt market misvaluation. We also use the market-to-book equity ratio to proxy for the mispricing of equity, the deviation of a firm's market value from its fundamental book value. We include standard control variables, such as the logarithm of total assets, profitability, tangibility, and market leverage. The market leverage is included because it is well known that firms actively adjust capital structure and that leverage ratio is mean-reverting (Leary and Roberts, 2005). Lastly, we consider the mispricing score from Stambaugh and Yuan (2017).[11] In all specifications, we control for both firm and time fixed effects. We require asset values greater than one million, and winsorize all the accounting variables at the bottom and top two percentiles.

[Insert Table 13 here]

[11]Detailed definitions of the variables can be found in Table 1.

4.1.1 Panel regressions

We report panel regression results in Panel A of Table 13. First, when the dependent variable is net equity issuance, the coefficient of DES is 0.12 with a *t*-statistic of 4.01 in the first specification. This positive coefficient confirms our intuition that firms issue more equities when their stocks are overvalued. Second, in the third specification where we include all the competing mispricing measures, the coefficient of DES remains largely the same. While the actual credit spreads and ME/BE show a weak impact, MispScore has a significantly positive effect on equity issuance. Third, the estimated coefficients of market leverage (MktLev) are the most significant among all the control variables considered, consistent with the mean reversion of capital structure documented in the literature. Overall, this indicates that our valuation gap measure carries the information about equity issuance beyond other mispricing measures and control variables.

We next examine the relation between DES and corporate net debt issuance. A few observations emerge. First, the negative coefficient of DES, –0.26 (*t*-statistic = –3.89), in the first specification suggests a significant reduction in debt for firms with high DES. It remains statistically significant after we include other control variables in the next two specifications. Second, the estimate of CS^{D} is positive, likely due to its high correlation with market leverage. Third, the negative coefficient of ME/BE is consistent with the idea that firms with overvalued equity prefer issuing equity than debt. Lastly, MispScore has a relatively weak effect on debt issuance, which is not surprising because it is derived from equity market anomalies.

The opposite signs in the DES coefficients in equity and debt issuance suggest that firms do time the markets by issuing equity to retire debt. However, the negative coefficient of DES for debt issuance more than double that for equity issuance, imply that firms might need additional funds to retire their debt. In the last panel where the dependent variable is the change in cash holdings, the significant, negative coefficients on DES indicate that high DES firms draw down cash to retire their undervalued debt.

Taken together, we find that DES is positively associated with net equity issuance, and negatively with net debt issuance and changes in cash holdings in the subsequent quarter. Interestingly, the online appendix shows that DES has no significant association with real capital investments or R&D investments. The latter finding can be because, in contrast to financial assets, real investments are costly to adjust and take time to build.

4.1.2 Logistic regressions

Despite the relation between DES and net equity and debt issuances in Panel A, Table 13, it is not clear whether firms arbitrage across equity and debt markets to take advantage of the valuation gap. Specifically, when equity is overvalued relative to debt, does a firm issue equity at the same time of retiring its debt?

We proceed to run logistic regressions to examine the arbitrage behavior of non-financial firms in Panel B. In the first panel of equity-debt swap, the dependent variable is an indicator variable that equals one if net equity issuance and debt retirement of the same firm occur simultaneously in the same quarter, and zero otherwise. In the first panel, DES has a significantly positive effect on the equity-debt swap across all the three specifications, whereas ME/BE and MispScore ($\mathrm{CS^D}$) show the same positive (negative) sign as in Panel A. In the second panel, the dependent variable is an indicator that equals one if the change of cash holdings and net debt issuance of the same firm are both negative. The DES coefficients are significantly positive and range from 2.99 to 3.16, confirming that the results in Panel A that the firms draw down their cash holding to retire debt.

In conclusion, we demonstrate the unique information content of DES across equity and debt markets. Complementary to Baker and Wurgler (2002), our results suggest that a firm could lower its leverage ratio by issuing equity and retiring debt, indicating that firms act as arbitrageurs to exploit the relative mispricing between the debt and equity markets. When DES is high and debt is relatively underpriced, firms even draw down cash to retire debt.

4.2 Insider trading

Corporate managers with private information on the company trade their equity-based compensation to maximize their own wealth.[12] In this subsection, we examine how DES is associated with subsequent insider trading. Our conjecture is that firms with high DES have more stock sales by their insiders.

We test this conjecture using filing information from Thomas-Reuters Insider Filings from 1986 to 2020. We focus on non-derivative 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 non-missing 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.[13]

[12]Evidence of informed insider trades can be traced back to Jaffe (1974). A non-exclusive list of works in this large literature includes Lee (1997), Lakonishok and Lee (2001), Bhattacharya and Daouk (2002), Jeng et al. (2003), and Cohen et al. (2012) among many others.

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

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. Lastly, we follow Guay et al. (2021) and include control variables of the previous quarter, namely, the logarithm of market capitalization, profitability, book leverage, market to book equity ratio (ME/BE). We also include industry and time fixed effects, and cluster standard errors at the firm level.

[Insert Table 14 here]

Table 14 reports panel results. When the dependent variable is the fraction of insider sales volume, the coefficients of DES range from 1.35 to 1.63, which implies an increasing selling among insiders of high DES firms. Second, the coefficient of DES remains statistically significant when we include mispricing score and use a shorter sample that end in 2016. Third, interestingly, while ME/BE suggests more insider selling, the negative estimate of MispScore effectively implies less sales made by insiders. The latter result may be surprising but can be due to the correlation between MispScore and other control variables such as ME/BE.

Our results are nearly identical when we change the dependent variable to the fraction of the insider sales. Moreover, in the online appendix, we use alternative sample, which include routine trades, and perform additional tests. These results in Table B6 are very similar to those in Table 14. Therefore, our results are not driven by the exclusion of "routine" trades.

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

5 Conclusion

In a structural model with no arbitrage, stocks and bonds of the same firm are expected to be priced consistently because both are contingent claims on the same underlying asset. In the data, the equity and debt markets can be segmented and disintegrated because of limits to arbitrage, generating a valuation gap. In this study, we propose a firm-level measure

years.

of valuation gap between equity and debt, the debt-equity spread (DES), and examine its implications for asset prices and corporate decisions.

Four main findings are worth emphasizing. First, DES predicts stock returns negatively but bond returns positively, which indicates that a higher DES is likely to be associated with an overvaluation in the stock price and undervaluation in the bond price. Second, firms with higher DES have high analyst-forecasted long-term earnings growth, which is then revised downward by subsequent negative surprises, suggesting that investors are over-optimistic about the prospect of high DES firms. Third, the return prediction of DES is stronger among stocks and bonds with higher limits to arbitrage. Fourth, firms with higher DES are followed by more equity issuance and debt retirement, and more stock sales by insiders.

This collective evidence indicates that our valuation gap measure, DES, is more likely to capture the relative mispricing between debt and equity, although we cannot completely rule out all risk-based explanations. This simple measure, which integrates information from equity and bond markets, can be of interest to researchers and institutions in studying relative mispricing cross-market. 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 valuation gap measure. We leave this agenda for our future study.

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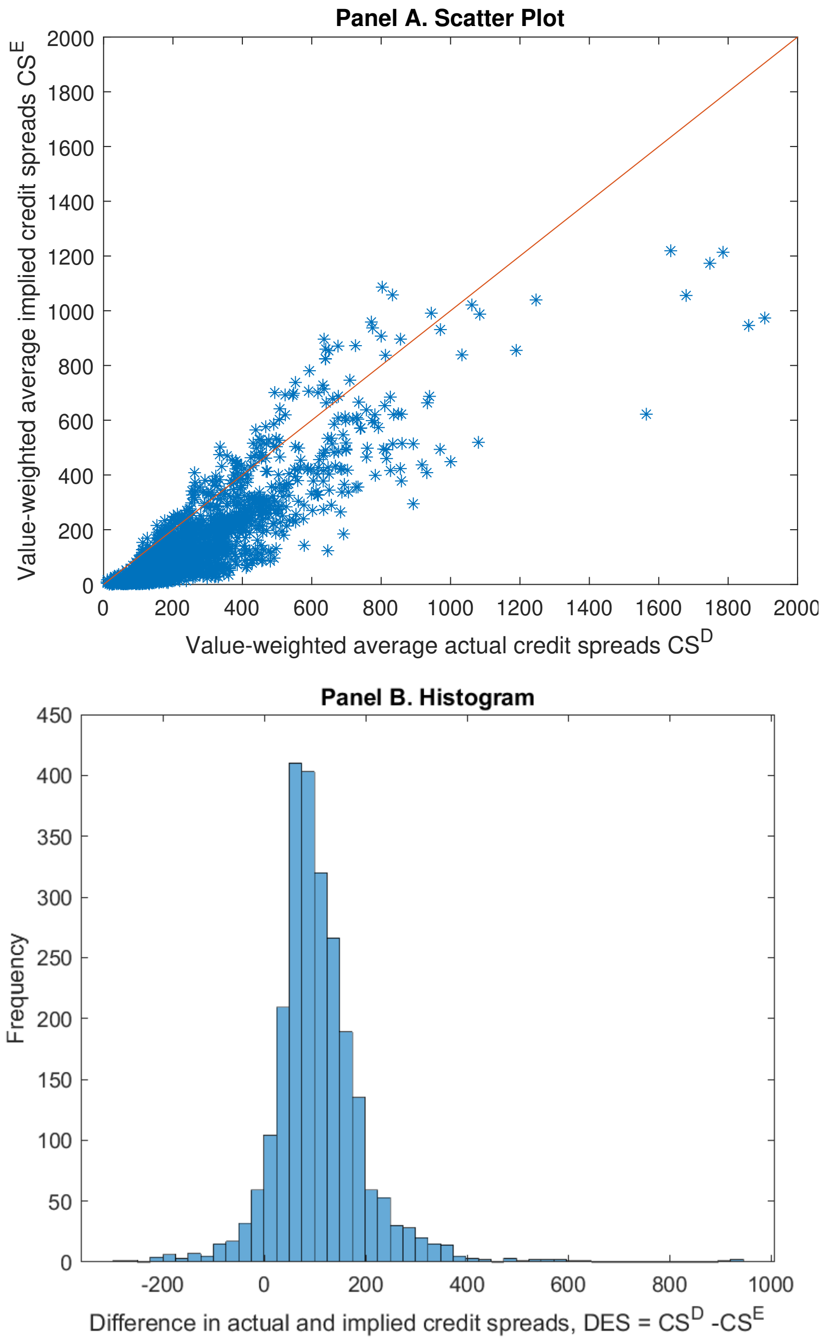

Figure 1: **Performance of the extended CreditGrades model**
Panel A plots the model implied credit spreads against actual credit spreads across five quintile portfolios sorted by actual credit spreads. Firm-level credit spreads (for both actual and implied) are computed as the bond market value weighted 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.

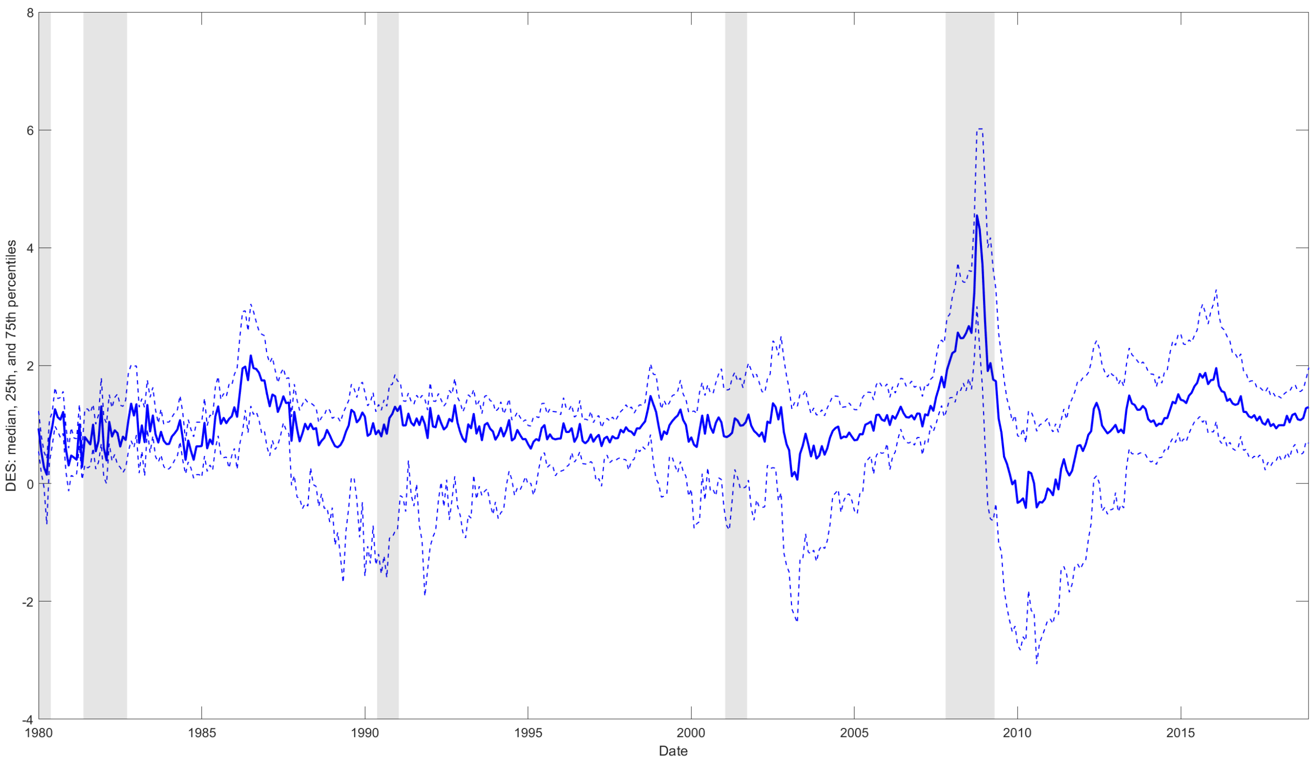

Figure 2: **Times series of DES distribution**
This figure plots the time series of median, 25th percentile, and 75th percentile of portfolio-level DES. The gray bars represent NBER recessions. The sample ranges from January 1980 to December 2020.

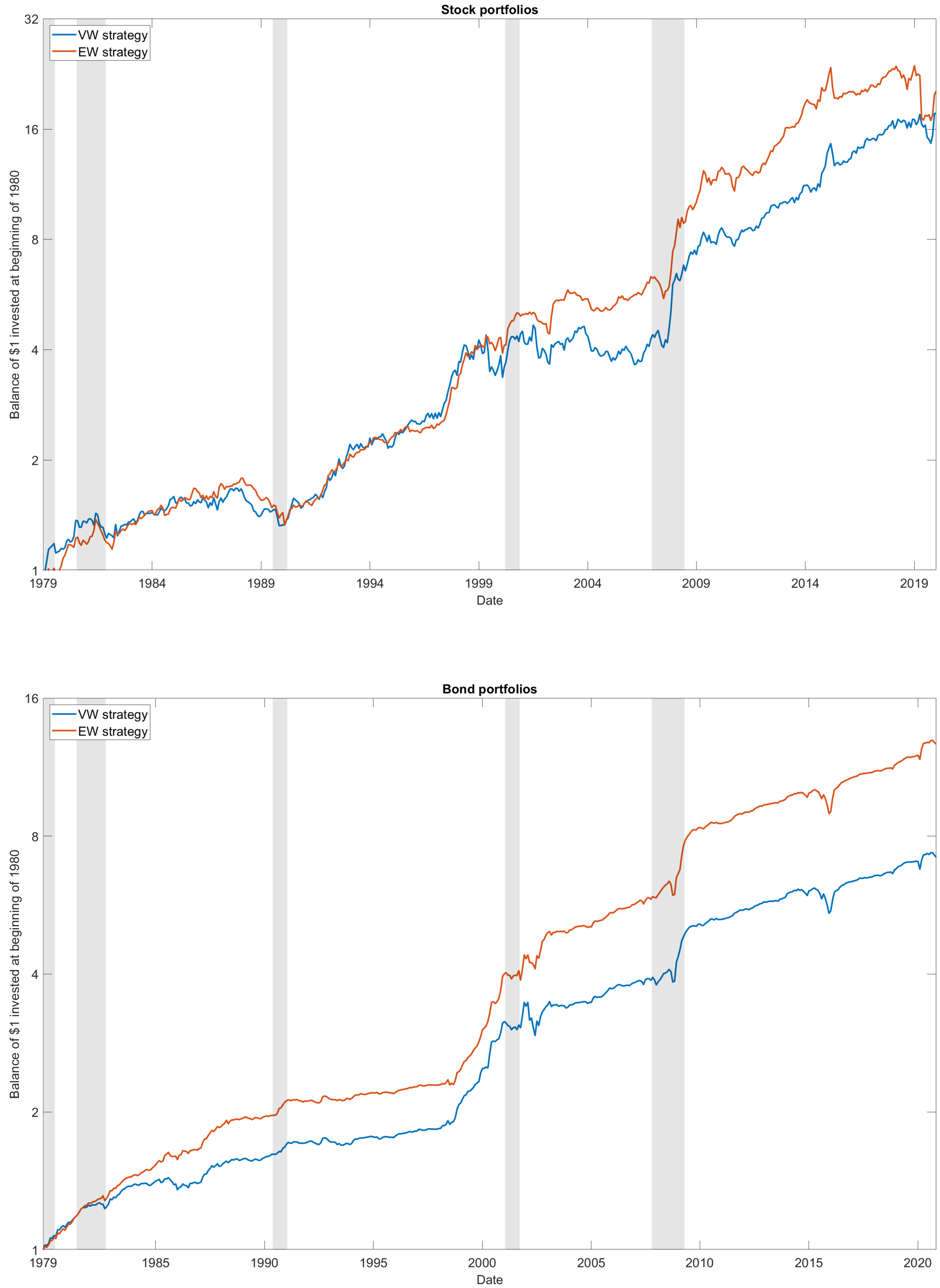

Figure 3: **Cumulative returns of DES long-short portfolios**
This figure plots the time series of the balance of $1 invested in the long-short DES portfolio at the beginning of 1980 for both the value-weighted (VW) scheme and equally-weighted (EW) scheme. The top panel is for the stock portfolios and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

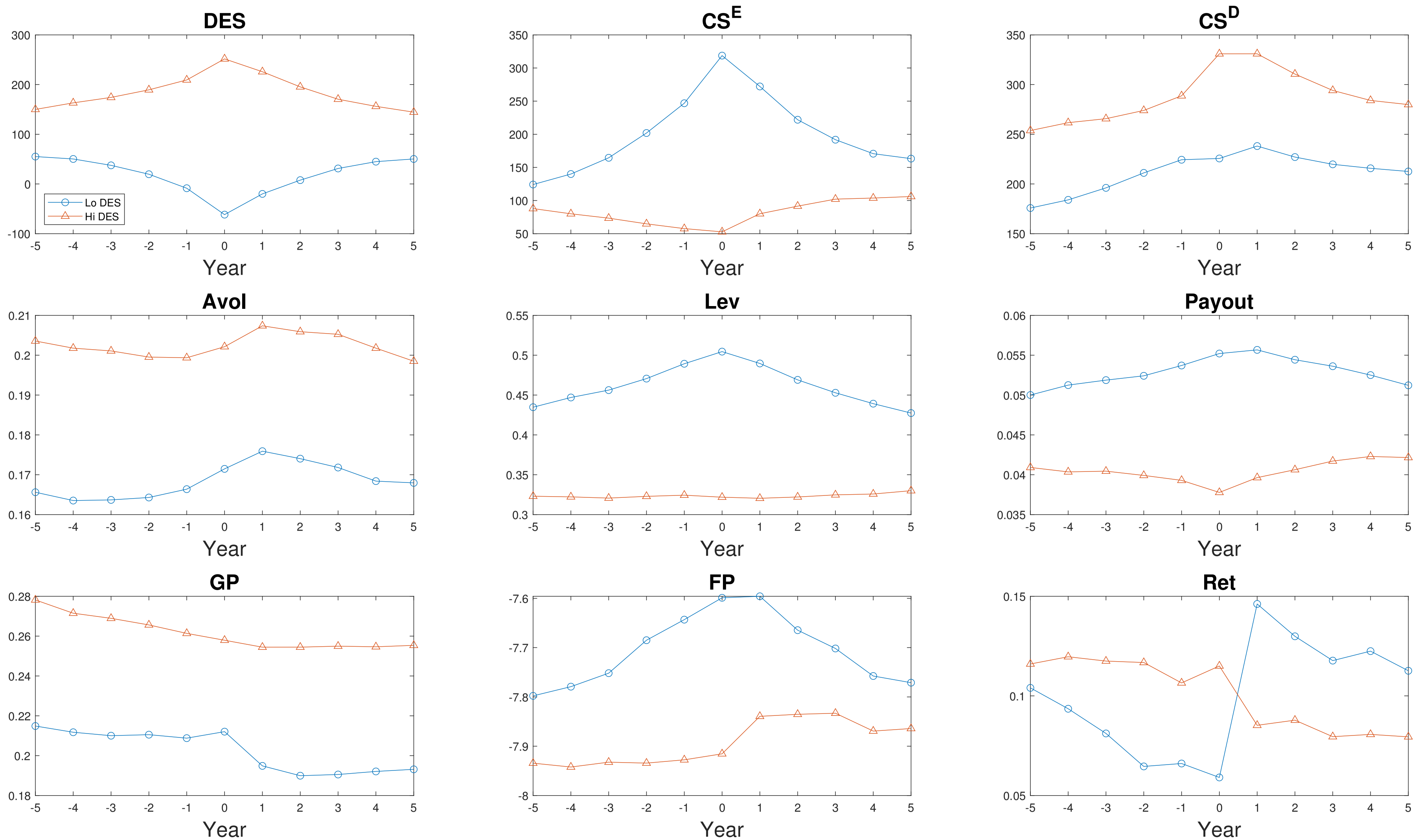

Figure 4: **Dynamics of characteristics for high and low debt-equity spread (DES) portfolios**
This figure plots the dynamics of the average firm-level variable 11 years around the portfolio rebalancing for high and low debt-equity spread (DES) quintile portfolios. These variables include the sorting variable, DES, implied credit spread (CS^E), actual credit spread (CS^D), asset volatility (Avol), financial leverage (Lev), Payout rate (Payout), gross profitability (GP), failure probability (FP), and stock returns (Ret).

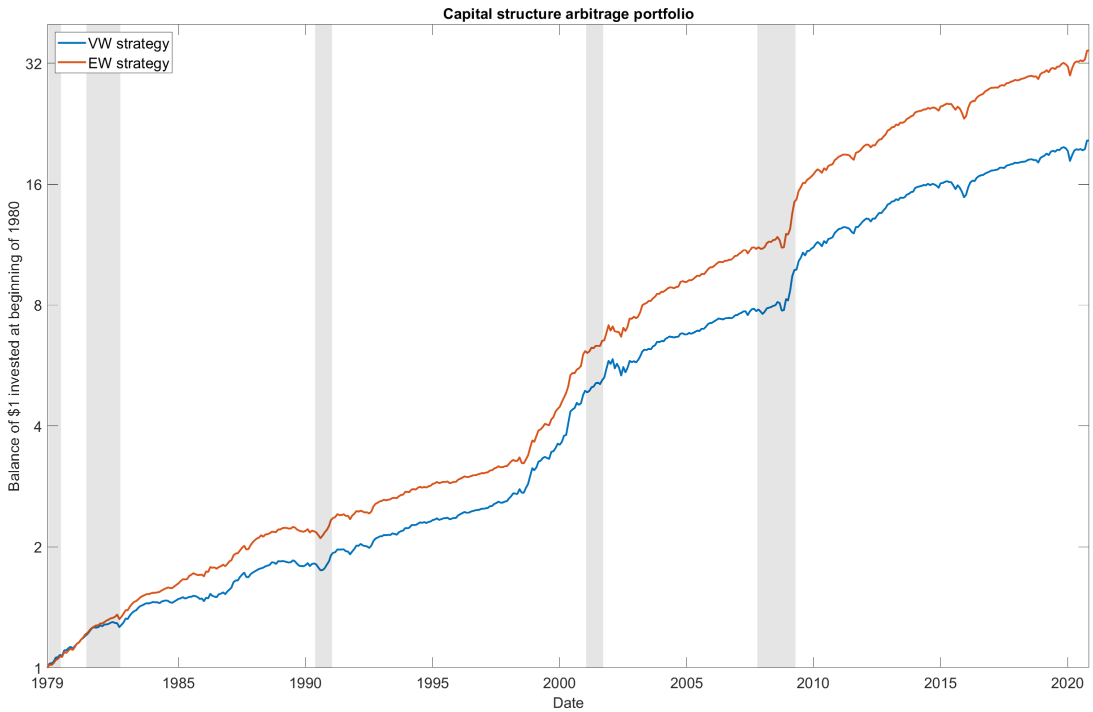

Figure 5: **Cumulative returns of DES capital structure arbitrage portfolios**
This figure plots the time series of the balance of $1 invested in the long-short DES capital structure arbitrage portfolio at the beginning of 1980 for both the value-weighted (VW) scheme and equally-weighted (EW) scheme. For each bond, we compute the return of a hedged position that buys the bond and short-sells the stock of the same firm using the estimated hedge ratio. We compute the average hedged returns for each DES quintile and plot the cumulative return of the long-short DES portfolio. The gray bars represent NBER recessions.

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

Variable	Definition
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 2-12 month cumulative returns (Source: CRSP)
Asset growth (AG)	Growth rate of total asset (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 during 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)	The standard deviation of forecasted earnings per shares in June of each year divided b stock price at the end of June (Source: IBES.)
Panel B. Bond characteristics	
Amihud's liquidity	the 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 during that month (Source: TRACE)
gamma	the negative of autocorrelation between prices (Bao et al., 2011) (Source: TRACE)

Number of trading days	the number of days that a bond has been traded within a month (Source: TRACE)
Panel C. Corporate Activities and Insider Trading	
Net equity issues	Equity issuance (Compustat item SSTKQ) minus equity repurchase (PRSTKCQ), divided by total assets (ATQ) of the previous quarter (Source: Compustat)
Net debt issues	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)
Insider sales	The ratio of shares sold to total number of shares traded by insiders each month (Source: Thomas-Reuters Insider Filings)
Log(BA)	Logarithm of total assets (item AT) (Source: Compustat)
Profitability	Operating incomes divided by total assets of last period (OIBDP/AT) (Source: Compustat)
Tangibility	Property, plants and equipments divided by total assets (PPENT/AT) (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)	The ratio of the market value of equity to its 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 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 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), the equity lending fee, measured by simple average fee from Markit (SAF), analyst forecast dispersion (FDisp), and mispricing score (MispScore) from Stambaugh, Yu, and Yuan (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 from January 1980 to December 2020.

Panel A. DES and its inputs					
	L(ow)	2	3	4	H(igh)
N	49.36	44.97	44.07	45.43	48.72
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

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) 3-factor model (FF3), Carhart 4-factor model (C4), Fama and French (2015) 5-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 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 due to the availability of the Bai et al. (2019) factors. We report the results using both value-weighted (VW) scheme and equally-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: **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 4-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 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 of July 2004 to June 2019. The full samples are described in Table 3, with the end of 1999 as the the cutoff date for the two subsamples. We report the results using both value-weighted (VW) scheme and equally-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 5: **Fama-MacBeth regressions**

This table reports the results from monthly Fama-MacBeth return predictive regressions. In Panel A, we run cross-sectional regression 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, and Stambaugh, Yu, and Yuan (2012) mispricing score (MispScore). In Panel B, we run bond returns on the bond-level DES, firm characteristics and bond characteristics, such as logarithm of bond size, amount outstanding, age, and coupon payment. 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 Specifications 7 and 8, which ends on December 2016 due to the data availability of MispScore.

Panel A: Stock returns

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

Panel B: Bond returns

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

Table 6: **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 regression 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 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)	(−1.38)	(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	−0.04				
						(1.26)	(−1.75)				
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 7: **Long-term earnings growth forecast revisions**

This table examines the relation between 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. 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 data is from January 1981 to December 2020.

Panel A: Average LTG					
	L(ow)	2	3	4	H(igh)
LTG	10.21	11.59	11.68	12.12	12.73

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 8: **The role of limits to arbitrage: Stock portfolios**

This table reports the average annualized value-weighted excess returns and Carhart 4-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 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								
	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 9: **The role of limits to arbitrage: Bond portfolios**

This table reports the average annualized value-weighted excess returns and Bai et al. (2019) 4-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 from January 1980 to December 2020 for bond size, Amihud illiquidity, and dollar volume, from August 2002 to December 2020 for Amihud illiquidity and bond gamma. All 4-factor model tests are performed between July 2004 and June 2019 due to 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

	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 10: **Bond illiquidity and stock DES premiums**

This table reports the average annualized value-weighted excess returns and Carhart 4-factor model 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 tradedays. The Newey-West t-statistics given in parentheses control for heteroskedasticity and autocorrelation based on a lag of 12. The sample is from August 2002 to December 2020.

Panel A. Bond Amihud illiquidity								
	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 11: **Risk factor exposures of DES portfolios**

This table reports the factor exposures 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 data are 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 12: **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 7-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 7-factor model tests, where the sample period is from July 2004 to December 2019 due to the availability of the Bai et al. (2019) factors. We report the results using both value-weighted (VW) scheme and equally-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 13: **Corporate security issuance and cash holdings**

This table reports results from panel regressions of quarterly net equity issuance, net debt issuance and change in cash holdings 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, the logarithm of total assets, profitability, tangibility, cash reserve, market leverage, and mispricing score (MispScore) (Stambaugh and Yuan, 2017). while controlling for firm, industry 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 industry and time fixed effects for logistic regressions in Panel B. 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, except for Specification (5), where the sample ends in 2016 due to the data availability of MispScore.

Panel A. Panel regressions

	Equity issuance			Debt issuance			Change in cash holdings		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
DES	0.12	0.12	0.08	−0.26	−0.26	−0.22	−0.23	−0.23	−0.17
	(4.01)	(4.05)	(2.71)	(−3.89)	(−3.91)	(−2.87)	(−3.69)	(−3.69)	(−2.60)
CS^D	−0.11	−0.10	−0.03	0.42	0.42	0.40	0.46	0.46	0.54
	(−2.93)	(−2.89)	(−0.96)	(5.24)	(5.18)	(4.14)	(5.46)	(5.48)	(5.79)
ME/BE		0.00	0.00		−0.00	−0.00		0.00	0.00
		(1.44)	(0.43)		(−2.41)	(−3.10)		(0.44)	(0.60)
MktLev	0.05	0.05	0.05	−0.25	−0.25	−0.26	−0.09	−0.09	−0.08
	(8.95)	(9.33)	(8.47)	(−18.05)	(−18.01)	(−15.93)	(−7.40)	(−7.38)	(−6.04)
log(BA)	−0.01	−0.01	−0.01	−0.02	−0.02	−0.01	−0.03	−0.03	−0.03
	(−5.94)	(−5.68)	(−5.25)	(−5.80)	(−5.94)	(−4.50)	(−8.65)	(−8.39)	(−7.09)
Profitability	−0.13	−0.13	−0.09	−0.32	−0.31	−0.31	−0.07	−0.08	−0.14
	(−4.53)	(−4.63)	(−3.55)	(−3.96)	(−3.74)	(−3.81)	(−0.61)	(−0.62)	(−0.98)
Tangibility	0.01	0.01	0.01	0.08	0.08	0.08	−0.03	−0.03	−0.05
	(1.11)	(1.21)	(1.07)	(5.18)	(5.01)	(4.38)	(−1.83)	(−1.79)	(−2.71)
Cash	−0.05	−0.05	−0.05	−0.13	−0.13	−0.16	−0.96	−0.96	−1.05
	(−4.61)	(−4.59)	(−4.70)	(−5.16)	(−5.17)	(−6.14)	(−15.59)	(−15.59)	(−17.81)
Dividend	−0.14	−0.15	−0.15	0.52	0.56	0.50	0.13	0.13	0.05
	(−2.26)	(−2.50)	(−2.51)	(6.26)	(6.71)	(5.61)	(1.23)	(1.17)	(0.38)
MispScore			0.03			−0.02			−0.02
			(5.47)			(−1.90)			(−2.73)
N_obs	46071	46071	37033	46071	46071	37033	46071	46071	37033
Adj. R^2	0.19	0.19	0.19	0.07	0.07	0.06	0.10	0.10	0.12

Panel B. Logistic regressions						
	Equity-debt swap			Cash reduction for debt retirement		
	(1)	(2)	(3)	(1)	(2)	(3)
DES	5.13	5.34	4.19	3.02	2.99	3.16
	(5.36)	(5.56)	(3.81)	(3.37)	(3.34)	(2.97)
CS^{D}	−8.91	−9.08	−7.86	−5.86	−5.84	−6.31
	(−7.60)	(−7.75)	(−5.85)	(−5.33)	(−5.31)	(−4.82)
ME/BE		0.05	0.07		−0.01	0.00
		(5.12)	(6.26)		(−0.72)	(0.02)
MktLev	2.21	2.36	2.35	2.32	2.30	2.38
	(14.29)	(14.98)	(13.39)	(16.01)	(15.61)	(14.15)
log(BA)	−0.01	−0.01	−0.07	0.16	0.16	0.16
	(−0.31)	(−0.20)	(−2.43)	(6.17)	(6.16)	(5.37)
Profitability	0.49	0.12	0.61	2.18	2.23	2.43
	(0.72)	(0.18)	(0.81)	(3.40)	(3.46)	(3.35)
Tangibility	−0.81	−0.73	−0.36	−0.65	−0.66	−0.43
	(−4.25)	(−3.81)	(−1.69)	(−3.60)	(−3.65)	(−2.08)
Cash	0.18	0.16	0.86	7.48	7.48	8.15
	(0.68)	(0.60)	(2.90)	(29.80)	(29.81)	(28.21)
Dividend	−5.03	−6.39	−4.29	−5.26	−5.08	−5.07
	(−3.89)	(−4.83)	(−2.88)	(−4.43)	(−4.18)	(−3.61)
MispScore			1.10			0.00
			(7.18)			(0.01)
N_obs	46178	46178	37121	46178	46178	37121
Pseudo R^2	0.01	0.01	0.01	0.03	0.03	0.03

Table 14: **Insider stock selling**

This table reports results from panel regressions of monthly insider sales on the 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 market capitalization, profitability, book leverage, and market to book equity ratio (ME/BE). We include (Fama-French 12) industry, 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 due to the data availability of MispScore.

	Fraction of insider sales volume			Fraction of insider sales		
	(1)	(2)	(3)	(1)	(2)	(3)
DES	1.62	1.63	1.35	1.63	1.64	1.36
	(3.51)	(3.56)	(2.62)	(3.57)	(3.62)	(2.63)
CS^D	−3.58	−3.58	−3.34	−3.56	−3.57	−3.27
	(−7.50)	(−7.53)	(−5.95)	(−7.26)	(−7.29)	(−5.73)
ME/BE		0.01	0.01		0.01	0.01
		(3.37)	(2.37)		(3.32)	(2.32)
MispScore			−0.20			−0.20
			(−4.25)			(−4.29)
log(Cap)	0.04	0.03	0.01	0.04	0.02	0.01
	(3.58)	(1.90)	(0.91)	(3.32)	(1.70)	(0.75)
Profitability	0.01	0.01	0.02	0.01	0.01	0.02
	(0.70)	(0.57)	(0.88)	(0.65)	(0.52)	(0.87)
Lev	−0.02	−0.12	−0.10	−0.03	−0.12	−0.10
	(−0.38)	(−1.82)	(−1.40)	(−0.43)	(−1.84)	(−1.41)
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 of "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 U.S. 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 non-convertible 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.

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 have special sales conditions.

A.2 Calculation of Bond returns

We use bond returns from Lehman Brothers Fixed Income Database for the period of January 1980 to June 1998, and RET_L5M from Wharton Research Data Services (WRDS) for the period of July 2002 to December 2020. For the rest of the sample, we use bond prices from NAICS and calculate the monthly bond excess 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 a monthly return are available in both scenarios.

B Robustness tests

B.1 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 2010s.

[Insert Table B1 here]

We first report the results on stock returns. As shown in Panel A of Table B1, 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, 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 become mostly larger after we control for the industry effects.

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 adopted 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 CDS trading and DES premiums

We examine the relation between CDS trading and DES premiums in Table B3. 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 B3 here]

However, the results in Table B3 indicate that the DES premiums remain strong in both subsamples with and without CDS tradings. 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 tradings on bond and equity markets documented in the literature, the DES premiums are not significantly affected by CDS tradings.

B.4 Time-to-maturity and bond DES premium

To further examine the role of the 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 the 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 B4 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 B4 here]

B.5 Long-horizon DES return prediction

Figure 4 indicates that DES can persist for several years. In this subsection, we look into long-horizon return prediction. We explore various holding periods ranging from one month to 60 months for the DES long-short portfolio.

The top two panels of Figure B.1 reports the average monthly buy-and-hold returns, Carhart 4-factor alphas, and their *t*-statistics against different holding periods. The top two panels show that the average stock return declines with the holding period, but the return spread remains sizable and statistically significant (t-statistic > 2.5), even five years after portfolio sorts. The bottom two panels show the results for bond portfolios. The average buy-and-hold bond return decays much faster than stock portfolios. It becomes only marginally significant 12 months following the portfolio rebalancing.

[Insert Figure B.1 here]

B.6 DES and corporate investments

We provide further evidence on corporate investments, including capital and research & development (R&D) investments in Table B5. Different from the results in Table 13, most of the coefficients of DES are economically and statistically insignificant. The difference indicates that, although they might take advantage of the relative 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 B5 here]

B.7 DES and insider trading

We report additional tests to validate our measure via corporate insider tradings in Table B6.

[Insert Table B6 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 14. Therefore, our results are independent of sample selection.

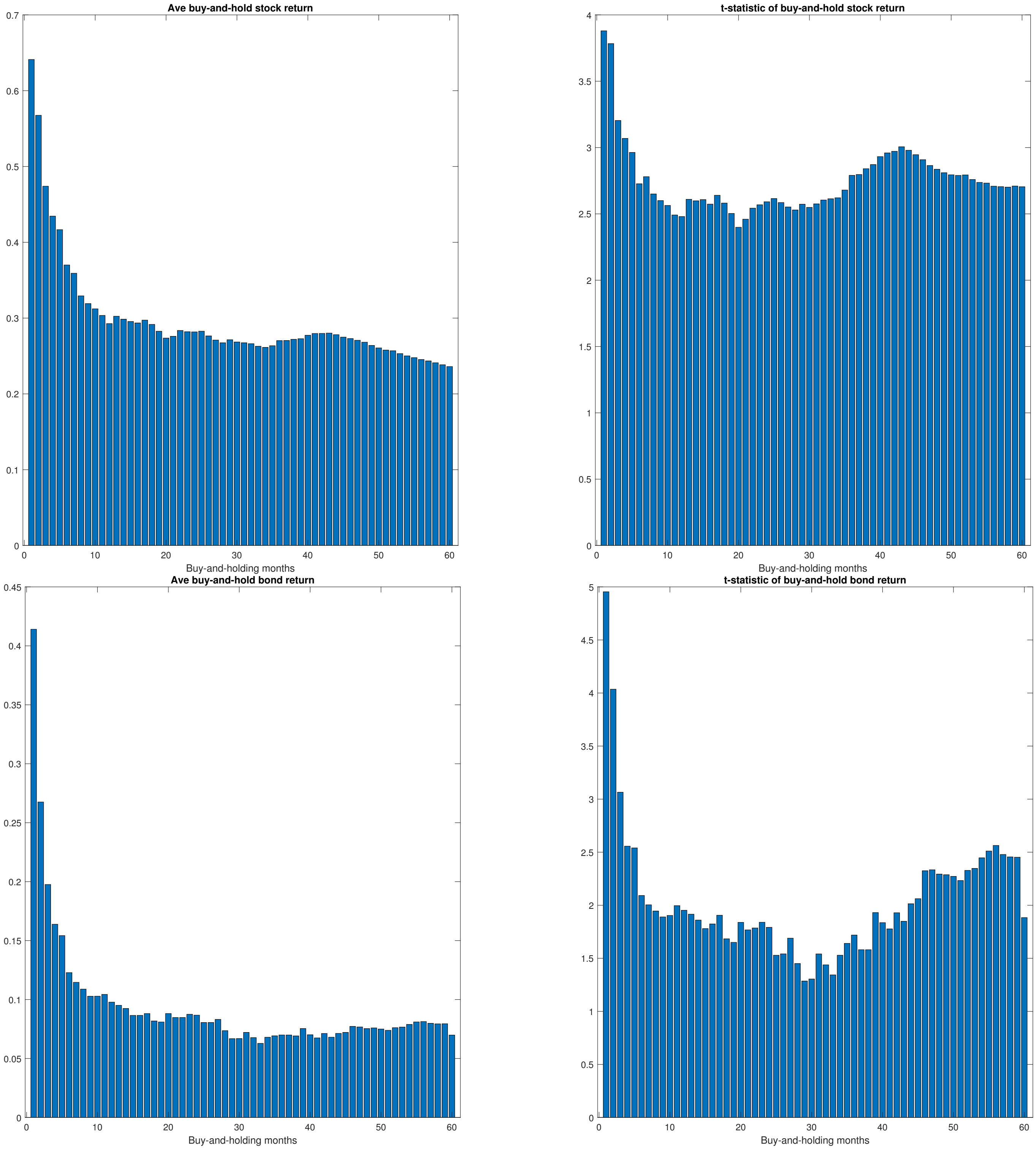

Figure B.1: **Long-term return prediction of debt-equity spread (DES)**
This figure plots the mean and t-statistics of monthly buy-and-hold returns of the long-short DES stock (top panels) and bond (bottom panels) portfolio for a holding period ranging from 1 to 60 months. t-statistics are based on Newey-West standard errors with lag = K+2 that control for heteroskedasticity and autocorrelation, where K is the predictive horizon. The sample is from January 1980 to December 2020.

Table B1: **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) 3-factor model (FF3), Carhart 4-factor model (C4), Fama and French (2015) 5-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 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 value-weighted (VW) scheme and equally-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 due 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 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) 3-factor model (FF3), Carhart 4-factor model (C4), Fama and French (2015) 5-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 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 due to the availability of the Bai et al. (2019) factors. We report the results using both value-weighted (VW) scheme and equally-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: **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) 3-factor model (FF3), Carhart 4-factor model (C4), Fama and French (2015) 5-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 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 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 due 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 B4: **Time-to-maturity and bond DES premiums**

This table reports the average annualized value-weighted excess returns and Bai et al. (2019) 4-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 4-factor model tests start in July 2004 due 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 B5: **Tangible and intangible investments**

This table reports results from panel regressions of quarterly net capital investments (Panel A), and changes in cash holding (Panel B) 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, the logarithm of total assets, profitability, tangibility, cash reserve, market leverage, and mispricing score (MispScore) (Stambaugh and Yuan, 2017), as well as firm, (Fama-French 12) industry, 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, except for Specification (5), where the sample ends in 2016 due to the data availability of MispScore.

Tangible and Intangible Investments						
	Capital investments			R&D investments		
	(1)	(2)	(3)	(1)	(2)	(3)
DES	−0.01	−0.01	−0.01	−0.02	−0.01	−0.01
	(−0.30)	(−0.23)	(−0.53)	(−2.38)	(−2.11)	(−1.42)
CS^D	−0.15	−0.15	−0.17	0.03	0.03	0.04
	(−4.57)	(−4.62)	(−4.59)	(3.76)	(3.62)	(3.52)
ME/BE		0.00	0.00		0.00	0.00
		(1.62)	(1.90)		(3.90)	(3.75)
MktLev	−0.08	−0.08	−0.08	−0.00	−0.00	−0.00
	(−14.00)	(−13.56)	(−13.12)	(−2.69)	(−1.82)	(−1.34)
log(BA)	−0.01	−0.01	−0.01	−0.00	−0.00	−0.00
	(−7.53)	(−7.50)	(−7.46)	(−2.01)	(−1.92)	(−1.28)
Profitability	0.10	0.10	0.09	0.03	0.02	0.03
	(4.00)	(3.87)	(3.37)	(2.89)	(2.51)	(2.33)
Tangibility	0.08	0.08	0.09	0.00	0.00	0.00
	(10.12)	(10.18)	(10.87)	(1.27)	(1.64)	(0.76)
Cash	−0.01	−0.01	−0.01	0.01	0.01	0.01
	(−0.92)	(−0.94)	(−0.50)	(1.53)	(1.48)	(1.29)
Dividend	−0.07	−0.08	−0.10	0.03	0.02	0.01
	(−1.65)	(−1.95)	(−2.30)	(1.83)	(0.91)	(0.71)
MispScore			0.01			−0.00
			(3.48)			(−1.26)
N_obs	45987	45987	36943	46178	46178	37121
Pseudo R^2	0.16	0.16	0.16	0.07	0.07	0.07

Table B6: **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 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 market capitalization, profitability, book leverage, and market to book equity ratio (ME/BE), as well as mispricing score (MispScore) (Stambaugh and Yuan, 2017). We include firm, (Fama-French 12) industry, 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 due to the data availability of MispScore.

	Fraction of insider sales volume			Fraction of insider sales		
	(1)	(2)	(3)	(1)	(2)	(3)
DES	1.96	1.97	1.57	1.97	1.99	1.58
	(3.81)	(3.84)	(2.79)	(3.85)	(3.88)	(2.77)
CS^D	−4.08	−4.07	−3.76	−4.05	−4.04	−3.67
	(−6.24)	(−6.27)	(−5.46)	(−6.04)	(−6.06)	(−5.26)
ME/BE		0.01	0.01		0.01	0.01
		(2.86)	(2.10)		(2.84)	(2.06)
MispScore			−0.25			−0.24
			(−4.24)			(−4.26)
log(Cap)	0.02	−0.00	−0.01	0.01	−0.00	−0.01
	(0.96)	(0.00)	(−0.56)	(0.82)	(−0.12)	(−0.63)
Profitability	0.02	0.01	0.02	0.01	0.01	0.02
	(0.63)	(0.56)	(0.83)	(0.60)	(0.53)	(0.83)
Lev	−0.01	−0.09	−0.08	−0.01	−0.09	−0.08
	(−0.10)	(−1.20)	(−1.01)	(−0.13)	(−1.23)	(−1.02)
N_obs	14877	14877	12536	14877	14877	12536
Adj. R^2	0.38	0.38	0.35	0.39	0.39	0.35