Switching Perspective: How Does Firm-Level Distress Risk Price the Cross-Section of Corporate Bond Returns? *

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Abstract

We document a significantly negative relation between firm-level distress risk and the cross-section of corporate bond returns, analogous to the often negative relation between distress risk and stock returns in the prior literature ("distress anomaly"). Our evidence casts doubts on theories attributing the distress anomaly to shareholders exploiting debtholders in distress ("shareholder advantage"). In accordance, shareholder advantage proxies do not condition the distress risk-bond return relation. Conversely, we show that real options theories with disinvestment also have the potential to explain the anomaly, with disinvestment proxies conditioning the relation between distress risk and both stock and bond returns.

JEL Classification: G11; G12.

Keywords: Distress risk, corporate bonds, shareholder advantage, disinvestment options.

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1 Introduction

Recent empirical work finds a flat, hump-shaped, or negative relation between the probability that a firm fails to honor its fixed obligations ("distress risk") and the cross-section of stock returns.[1] The most convincing explanation for that finding is Garlappi et al.'s (2008) and Garlappi and Yan's (2011) shareholder advantage theory, which argues that shareholders' ability to extract economic rents from debtholders in default lowers stock risk and thus the returns of distressed stocks. Further evidence supporting that theory comes from Favara et al. (2012), who show that stock betas and volatilities are lower in countries whose institutions favor shareholders over debtholders, and Aretz et al. (2018), who show that the distress risk-stock return relation is more negative in the same countries. Also, Hackbarth et al. (2015) find that an exogenous increase in shareholder advantage in the United States in 1978 lowered stock betas and returns for all but most strongly distressed firms.

In our paper, we document that, analogous to the non-positive and often negative relation between firm-level distress risk and the cross-section of stock returns in the prior literature, there is also a negative relation between firm-level distress risk and the cross-section of corporate bond returns. In particular, using Campbell et al.'s (2008) hazard model to capture the probability of failure (defined as a default, bankruptcy filing, or performance-related delisting),[2] we find a monthly distress premium in bonds of –30 to –50 basis points in both portfolio sorts and Fama-MacBeth (FM; 1973) regressions. Akin to stocks, the premium is, however, only statistically significant when we control for popular stock and bond pricing factors, such as the bond market beta and bond-price momentum (see Bai et al. (2018), Bali et al. (2019a) and Bali et al. (2019b)). Finally, the negative premium is attributable to inter-firm variations in distress risk. Keeping firm-level distress risk constant, intra-firm variations in distress risk due to variations in bond indentures (as, e.g., in seniority, coupons, or collateral) are typically positively priced.

Our evidence that distress risk is negatively priced in corporate bonds comprises a serious blow to the shareholder advantage theory. The shareholder advantage theory starts from the premise that debtholders are entitled to a perpetual stream of coupon payments, but that they have awarded shareholders the option to cease payments in return for a to-be-negotiated fraction of firm value. Given that the option

[1] See, for example, Dichev (1998), Campbell et al. (2008), and Da and Gao (2010).

[2] A large literature suggests that hazard-model predictions of failure in general — and Campbell et al.'s (2008) prediction in particular — are vastly superior to, for example, discriminant-analysis or structural model-based predictions (see Shumway (2001), Chava and Jarrow (2004), Bharath and Shumway (2008), Campbell et al. (2008), and Aretz et al. (2018)).

issued by debtholders is a perpetual American put option, its systematic risk — if held short — increases with the option exercise probability, which is equivalent to distress risk. Thus, the shareholder advantage theory predicts that the expected debt return increases with distress risk. To put that intuition on a more formal footing, we extend the simulation evidence of Garlappi et al. (2008), who employ Fan and Sundaresan's (2000) shareholder advantage model to create an artificial cross-section of expected stock returns and distress risk under realistic model inputs. Doing so, they find that high shareholder advantage can turn the expected stock return-distress risk relation negative. Picking up where they left off, we, however, show that the expected debt return-distress risk relation is consistently positive in their simulations, confirming that shareholder advantage cannot explain our bond pricing evidence.

To further show that shareholder advantage is not behind our bond evidence, we next condition the bond distress premium on popular shareholder advantage proxies, such as research and development (R&D) expenses, the Herfindahl sales index, and asset tangibility (see Garlappi et al. (2008) and Favara et al. (2012)). Since lower R&D expenses predict fewer cash-flow-related debt covenants, while a higher Herfindahl index and a lower asset tangibility predict greater fire-sale discounts in distress, low R&D expenses, a high Herfindahl index, and a low asset tangibility indicate high shareholder advantage. Double-sorted portfolios and FM regressions with interaction terms suggest that, while the shareholder advantage proxies usually continue to condition the distress risk-stock return relation (even within our smaller data sample), they are completely powerless to condition the distress risk-bond return relation. To make matters worse, the proxies tend to condition the bond distress premium with the wrong signs.

Given the limited success of the shareholder advantage theory to yield a unified explanation for the pricing of distress in stocks and bonds, we next take a fresh look at what could lie behind the distress anomaly. As first pointed out by Guthrie (2011), the relation between the expected return on a claim of a firm and the firm's condition is jointly determined by asset and financial risk in neoclassical finance models. Focusing on asset risk, Hackbarth and Johnson (2015), Aretz and Pope (2018), and Gu et al. (2018) show that real-asset disinvestment options can lower the expected asset return of economically distressed firms because the disinvestment options can be interpreted as American put options with a negative systematic risk. Interestingly therefore, Table 2 in Campbell et al. (2008) suggests that firms classified by them as distressed are, on average, not only more financially levered but also less profitable than other firms.[3] It is thus entirely possible that a low asset risk, spurred by highly valuable negative systematic risk disinvestment options, lies behind the distress anomaly in both stocks and bonds.

We use numerical methods to value an equity claim and a zero-coupon debt claim on a firm owning production assets with embedded disinvestment options to study whether disinvestment risk can explain the distress anomaly. Assuming disinvestment proceeds go to shareholders unless they fall into a "suspect period" shortly before a debt default, in which case they go to debtholders, the model can produce a hump-shaped relation between distress risk and both stock and bond returns, which is more consistent with the empirical evidence than the shareholder advantage theory. To offer some more support for asset risk driving the distress anomaly, we then condition the stock and bond distress premia on Novy-Marx's (2013) gross profitability and Aretz and Pope's (2018) capacity overhang, defined as the difference between a firm's installed production capacity and its ex-ante optimal capacity.[4] While the first proxy measures economic profitability, the second measures how close a firm is to exercising its real-asset disinvestment options and thus also the value of these options. Double-sorted portfolios and FM regressions with interaction terms suggest that, with one exception, both gross profitability and capacity overhang significantly condition the relations between distress risk and both stock and bond returns with the correct signs.

Our work adds to studies on the distress premium in stocks. Dichev (1998), Griffin and Lemmon (2002), and George and Hwang (2010) show that Altman's (1968) Z-Score and Ohlson's (1980) O-Score, two accounting distress risk proxies, are flat in or decrease with stock returns. Extracting a distress risk proxy from Merton's (1974) model, Vassalou and Xing (2004) find a positive premium. Da and Gao (2010), however, question that premium, arguing it is attributable to illiquid stocks. Using the alternative structural distress risk proxy of Moody's KMV Corporation, Garlappi et al. (2008) and Garlappi and Yan (2011) find a hump-shaped relation between distress risk and stock returns. Anginer and Yildizhan (2018) report that corporate credit spreads, which increase with risk-neutral distress risk, do not price stocks. Avramov et al. (2009) show that stock returns increase with credit ratings, implying a negative distress risk-stock return relation. Using an efficient hazard model proxy, Campbell et al. (2008) report a negative distress premium in stocks. We contribute to those studies by showing that, analogous to the

[3] Given that Campbell et al.'s (2008) profitability variable, NIMTA, contains financial expenses, it is not a pure proxy for *economic* profitability. Using operating profitability, defined as the difference between sales and costs of gold sold scaled by total assets, we, however, find that operating profitability also strongly declines over their distress risk portfolios.

[4] Aretz and Pope (2018) define the ex-ante optimal capacity as that capacity level equalizing the marginal benefit of assets-in-place with the marginal cost of exercising growth options. See their paper for more technical details. An updated version of the capacity overhang proxy can be downloaded from: <https://www.kevin-aretz.com>.

often negative stock distress premium, the corporate bond distress premium can also be negative.

We also add to the literature by coming up with a new rationale for why both stock and bond returns decrease with distress risk. Prior studies often argue that financial risk lies behind the negative stock distress premium. As we already said, Garlappi et al.'s (2008) and Garlappi and Yan's (2011) shareholder advantage theory is the best-known example in that literature. Other examples include George and Hwang (2010), who reason that firms with high systematic risk induced through high financial distress costs endogenously choose low financial leverage ratios, and O'Doherty (2012), who speculates that high asset-value uncertainty drives down the systematic risk of distressed stocks. One caveat about these theories is that they often implicitly predict opposite effects of distress risk on stock and bond returns, inconsistent with our main empirical evidence. In contrast, we propose a real-asset based explanation for the distress anomaly suggesting that both stock and bond returns decline with distress risk.

We proceed as follows. Section 2 describes our analysis variables and data sources. In Section 3, we study the relations between distress risk and the cross-sections of corporate bond, stock, and asset returns. In Section 4, we investigate whether the shareholder advantage theory explains our empirical findings. Section 5 explores whether real-asset disinvestment risk explains them. Section 6 gives the results from several robustness tests. Section 7 summarizes and concludes our paper.

2 Methodology and Data

In this section, we describe our methodology and data. We first outline the hazard model and credit ratings used to measure distress risk at the firm- and the bond-level, respectively. We next explain how we calculate the returns on bonds and other assets. We finally discuss our data sources.

2.1 Calculating Firm- and Bond-Level Distress Risk

We follow Campbell et al.'s (2008) hazard model methodology to measure twelve-month-ahead firm-level distress risk. In particular, we estimate a logit model of a dummy variable equal to one if a firm defaults on its debt obligations, files for bankruptcy, or delists for performance reasons over the next twelve months and else zero, *Failure*, on distress risk predictors measured at the start of the twelve-month period.[5] We

[5] Shumway (2001) shows that a logit model is a special form of hazard model.

can compactly write the logit model as:

$$\text{Prob}(Failure_{i,t} = 1|\mathbf{X}_{i,t-12}) = \frac{1}{1 + \exp(-\alpha - \beta\mathbf{X}_{i,t-12})}, \tag{1}$$

where α is a free parameter, β a vector of free parameters, and $\mathbf{X}_{i,t-12}$ a vector containing the distress risk predictors. Campbell et al. (2008) estimate logit model (1) recursively, using data from January 1963 to December of calendar year t, with t ranging from 1980 to 2003 in unit increments. They next combine the logit model estimates obtained from the estimation window extending to December of calendar year t with the distress risk predictor values over calendar year $t+1$. Doing so, they ensure that the logit model prediction could have been computed by investors in real-time.

The distress risk predictors in $\mathbf{X}$ contain *NIMTA*, the ratio of net income to the sum of the market value of equity and the book value of total liabilities ("market-value-adjusted total assets"); *TLMTA*, the ratio of the book value of total liabilities to market-value-adjusted total assets; *CASHMTA*, the sum of cash and short-term assets to market-value-adjusted total assets; and *MB*, the market-to-book ratio. To mitigate the effects of outliers on *MB*, Campbell et al. (2008) add 10% of the difference between the market value and the book value of equity to the book value of equity, setting book values of equity that continue to be negative to $1. The vector $\mathbf{X}$ further contains *EXRET*, the monthly log stock return minus the monthly log S&P 500 return; *SIGMA*, a stock's volatility obtained from daily data over the prior three months;[6] *SIZE*, the log ratio of a stock's market capitalization to the S&P 500's total market capitalization; and *PRICE*, the log stock price truncated at $15.

To enhance the distress risk predictors' timeliness, Campbell et al. (2008) use quarterly accounting data in their calculations, assuming that the accounting variable values become publicly available with a two-month reporting gap (i.e., two months after the end of the fiscal quarter). To guard against outlier effects, they winsorize the distress risk predictors at the $5th$ and $95th$ percentiles.[7]

[6] More specifically, they calculate volatility as the square root of 252 times the average of the squared daily stock return over the prior three months, assuming that the expected daily stock return is equal to zero. In case of stocks with fewer than five non-zero returns over the three-month period, they replace the volatility estimate with the cross-sectional mean of the volatility estimates of stocks with more than five non-zero returns over the same period.

[7] Since we do not have access to the failure data used by Campbell et al. (2008), we are unable to estimate logit model (1) ourselves. Fortunately, however, Jens Hilscher sent us the output from recursively estimating that model as described in the text. We use the logit model output obtained from the longest estimation window (1980-2008) to calculate our firm-level distress risk proxy for the post-2010 sample period. Doing so is unlikely to cause problems since the recursive estimates sent to us show strong signs of converging over the sample period extending to 2008. We thank Jens Hilscher and his co-authors for sharing the estimation output from their recursive logit model estimations with us.

We rely on corporate bond ratings issued by Moody's and S&P's to measure intra-firm variations in distress risk induced through the characteristics of a bond issue — as opposed to the inter-firm variations captured by the firm-level distress risk proxy. To that end, we follow Bai et al. (2018) and assign a number to different ratings. In particular, we assign a value of one to AAA ratings, a value of two to AA+ ratings, and so on, until ultimately assigning a value of 21 to C ratings. As a result, investment-grade bonds have a value between one (AAA) and ten (BBB–), while non-investment-grade bonds have a value above ten. We finally compute *Rating* as the value associated with the most recent rating if only one agency issues ratings or the average of the most recent values if both agencies issue ratings.

2.2 Calculating the Returns on Corporate Bonds and Other Assets

In line with Bessembinder et al. (2009), Bao et al. (2011), and Jostova et al. (2013), we calculate the net return of corporate bond i over month t, $r_{i,t}$, using:

$$r_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1, \tag{2}$$

where P is the bond price, AI the accrued interest, and C the coupon payment. The price P is calculated as follows. To minimize confounding effects arising from bid-ask spreads, we start by calculating a bond's daily price as the trading-volume-weighted average of intra-day transaction prices over that day, as also done by Bessembinder et al. (2009). In line with Bai et al. (2018), we next calculate two types of bond returns, namely: (i) the return from the start of month t to the end of month t; and (ii) the return from the start of month t to the start of month $t+1$, where we define the start (end) of a month as the first (last) five trading days within that month. If we have more than one non-missing daily bond price within either the start- or end-of-month window, we choose the daily price closest to the first/last trading day of a month in our calculations. Finally, if we are able to calculate both types of returns, we use the start-of-month to start-of-month (type (ii)) return in our empirics.

To calculate the accrued interest AI, we first compute the daily coupon rate. The daily coupon rate is the coupon rate divided by 360 if a bond's day-count basis is "30/360" or "ACT/360," and it is the coupon rate divided by the actual number of calendar days per year if the day-count basis is "ACT/ACT." We next count the calendar days between the current month-end t and the previous coupon payment date, assuming that a month has 30 calendar days if the day-count basis is "30/360" and the actual number of days per month when it is "ACT/360" or "ACT/ACT." Also, we use the date of the first coupon payment and the coupon payment frequency to infer on which days the coupons are paid. We finally calculate the accrued interest AI as the daily coupon rate multiplied by the number of days between the current month-end t and the previous coupon payment date.

As is standard in the literature, we impose the following filters on our bond return data. First, we remove bonds not traded or listed in U.S. public markets. Second, we exclude bonds that are structured notes, are mortgage-, asset-, or agency-backed, or are equity-linked. Third, we remove convertible bonds. Fourth, we remove bonds with a price below $5 or above $1,000. Fifth, we keep only fixed and zero coupon bonds. Sixth, we remove bonds with less than one year to maturity. Seventh, we eliminate bond transactions that are labeled as when-issued or lock-in or have special sales conditions. Eighth, we remove transaction records that are canceled, subsequently corrected, or reversed. Finally, we only keep transactions with a trading volume that is larger than $10,000.

In addition to bond returns, we also investigate the stock returns of the subsample of firms with bonds outstanding over our bond sample period (July 2002 to June 2017). While we directly obtain the stock returns from CRSP, we replace a stock's return over its delisting month with its delisting return if the delisting return is non-missing. If a stock's return over its delisting month is missing, we replace the return with –30% for NYSE and AMEX stocks and –55% for NASDAQ stocks, as advocated by Shumway (1997) and Shumway and Warther (1999). We do not exclude stocks with low prices from the stock subsample associated with our bond sample since only large well-capitalized firms issue bonds, rendering that restriction unnecessary. When we later, however, shift our focus to a more comprehensive cross-section of stocks, we exclude stocks with a one-month-lagged price below $1.

We finally also take a look at a firm's asset return, defined as the return to both its shareholders and debtholders. Since we are unable to observe the return on private debt, we approximate the asset return using a value-weighted average of the returns on a firm's stock and its outstanding bonds, using either the book or market leverage ratio to derive the weights. We assume that firms have only common stock outstanding (i.e., we ignore preferred stock), and we calculate the return on outstanding bonds as the value-weighted average of the returns on all of the firm's outstanding bond issues. In line with Fama and French (1992), we define the book leverage ratio as the ratio of the book value of assets to the book value of equity, while we define the market leverage ratio as the ratio of the book value of assets to the market value of equity, using the sum of common equity plus balance-sheet deferred taxes as book value of equity. We use the ratios from the fiscal year ending in calendar year $t-1$ to calculate weights from July of calendar year t to June of calendar year $t+1$.

2.3 Calculating Risk Factors and Control Variables

We use portfolio sorts and FM regressions to investigate the pricing of distress risk. In the portfolio sorts, we adjust for risk by regressing a portfolio's return on risk factors and reporting the intercept from that regression ("alpha"). As risk factors, we choose either the Fama and French (1993) five-factor model factors or the Bai et al. (2018) nine-factor model factors. The five Fama-French (1993) factors are the excess stock market return ($\text{MKT}^{\text{Stock}}$), the returns of stock spread portfolios formed on size (SMB) and the book-to-market ratio (HML), as well as the returns of bond spread portfolios formed on the term structure (TERM) and default risk (DEF). The term structure spread portfolio is long on long-term government bonds and short on one-month Treasury bills. Conversely, the default risk spread portfolio is long on long-term corporate bonds and short on long-term government bonds. The nine Bai et al. (2018) factors add to the former five factors the return on a stock spread portfolio on momentum ($\text{MOM}^{\text{Stock}}$), Pastor and Stambaugh's (2003) stock liquidity risk factor (LIQ), the excess bond market return (MKT^{Bond}), and the return on a bond momentum spread portfolio (MOM^{Bond}). The excess bond market return is the return on a value-weighted portfolio of our sample bonds minus the one-month Treasury-bill rate. The bond momentum spread portfolio is long an equally-weighted portfolio of bonds with a past return over months $t-6$ to $t-1$ in the top decile and short an equally-weighted portfolio of bonds with that past return in the bottom decile (see Jostova et al. (2013)).[8]

In the FM regressions, we control for risk by including both stock and bond factor exposures and characteristics as control variables in our estimations. In particular, the bond-return regressions include a bond's exposures to the excess stock ($\text{MKT}^{\text{Stock}}$) and bond ($\text{MKT}^{\text{Bond}}$) market returns and to the SMB, HML, $\text{MOM}^{\text{Stock}}$, MOM^{Bond}, TERM, DEF, and LIQ spread portfolio returns. They further include a bond's years-to-maturity, log bond amount outstanding, most recent credit rating, and lagged one-month excess return. Conversely, the stock regressions include a stock's exposures to the excess stock and bond market returns and to the MOM^{Bond}, TERM, DEF, and LIQ spread portfolio returns,

[8] To avoid losing the first seven months of our sample period, we use the bond momentum spread portfolio return from Gergana Jostova's website over the July 2002-January 2003 period in our empirical work.

while directly adding the stock's one-month-lagged log market value of equity, log book-to-market ratio, and past-eleven-month compounded return.[9] In case of both the stock and bond portfolios, we estimate the exposures using rolling window regressions over the past 36 months of monthly data, winsorizing the estimated exposures at the $1st$ and $99th$ percentiles per month to mitigate outlier effects.

2.4 Data Sources

We obtain stock data from CRSP and accounting data from Compustat. We collect bond data, including intraday transaction prices, trading volumes, and buy and sell indicators, from the enhanced version of the Trade Reporting and Compliance Engine (TRACE). In contrast to the Lehman Brothers Fixed Income Database, Datastream, and Bloomberg, which are quote-based databases, TRACE is a trade-based database, offering higher market transparency (see Bessembinder et al. (2006)) and covering about 99% of all public bond-market transactions since February 2005 (see Bao et al. (2011)). We rely on the Mergent Fixed Income Securities Database (FISD) to obtain bond characteristics, including offering-amount and -date, maturity date, coupon-rate, -type, and -payout frequency, bond-type, -rating, and -option features, and issuer information. We obtain $\text{MKT}^{\text{Stock}}$, SMB, HML, and $\text{MOM}^{\text{Stock}}$ from Ken French's website, while we obtain LIQ from Lubos Pastor's website. We retrieve the corporate and government bond portfolio returns underlying the bond risk factors TERM and DEF from DataStream.

Our main bond sample period, determined by the availability of TRACE data, is July 2002 to June 2017. In our stock tests, we, however, sometimes rely on the longer sample period from January 1981 to December 2017, which is determined by our firm-level distress risk proxy.

3 The Pricing of Distress Risk in Corporate Bonds

In this section, we study the relation between firm-level distress risk and the cross-section of corporate bond returns. We start with offering summary statistics on our analysis variables. We next provide the

[9] Following Fama and French (1992), we calculate the log book-to-market ratio as the log of the ratio of the book value of equity to the market value of equity, where the book value of equity is total assets minus total liabilities plus deferred taxes minus preferred stock from the fiscal year-end in calendar year $t-1$ and the market value of equity is the stock price times shares outstanding at the end of calendar year $t-1$. We use the computed value from July of calendar year t to June of calendar year $t+1$. Following Carhart (1997), we calculate the past-eleven-month momentum return as the compounded return over months $t-12$ to $t-2$, leaving a one-month gap between the compounding period and the current month t to avoid that the momentum return also captures short-term reversal effects.

mean excess returns and alphas of bond portfolios and their associated stock portfolios univariately sorted based on our firm-level distress risk proxy. We finally report the same statistics for bond portfolios double-sorted on both the firm-level distress risk proxy and intra-firm distress risk as captured by bond ratings as well as asset portfolios univariately sorted on firm-level distress risk.

3.1 Summary Statistics

Table 1 reports summary statistics on our analysis variables, with Panels A, B, and C focusing on bond, stock, and firm characteristics, respectively. The summary statistics include the number of observations, the mean, standard deviation, and the $1st$, $5th$, $25th$, $50th$, $75th$, $95th$, and $99th$ percentiles. The table shows that our bond sample contains 556,965 bond-month observations over the sample period from July 2002 to June 2017. While the number of observations in our sample appears low compared to the number of observations used in other studies, we note that we lose many observations in the process of merging with the stock and firm characteristics data.[10] The average bond in our sample has a monthly return of 0.62%, a rating of 7.49 (BBB+), a market size of 0.57 billion dollars, and a time-to-maturity of 9.63 years. Conversely, the average stock has a monthly return of 0.96% and a market size of 58.6 billion dollars. The average twelve-month-ahead distress risk of the firms in our sample is only 0.09%, which is much lower than the average reported in Campbell et al. (2008). The reason is that bonds are almost exclusively issued by large firms, which tend to have a low distress risk.

Insert Table 1 here.

3.2 Portfolios Univariately Sorted on Firm-Level Distress Risk

We next analyze the relation between firm-level distress risk and the cross-section of corporate bond returns. To do so, we sort our bond sample into portfolios according to the decile breakpoints of the firm-level distress risk proxy distribution at the end of month $t-1$. We value- or equally-weight the portfolios, using the notional bond value outstanding at the end of month $t-1$ to calculate the value weights, and hold the portfolios over month t. We follow an analogous procedure to also sort the subsample of stocks associated with the bonds into value- or equally-weighted portfolios, using

[10]More specifically, our initial bond return sample contains 826,845 bond-month return observation, so that 269,880 observations are lost in the process of merging.

the market value of equity at the end of month $t-1$ to calculate the value weights. For each set of portfolios (i.e., the value or equally-weighted stock or bond portfolios), we create a spread portfolio long the highest distress risk portfolio and short the lowest portfolio. To adjust for systematic risk, we regress each portfolio's return on the five Fama and French (1993) factors or the nine Bai et al. (2018) factors introduced in Section 2.3 and report the alphas from these regressions.

Table 2 presents the mean excess returns, alphas, and other characteristics of the stock and bond distress portfolios, with Panel A focusing on the value-weighted and Panel B on the equally-weighted portfolios. Plain numbers are estimates, whereas the numbers in square parentheses are t-statistics calculated using Newey and West (1987) standard errors with a lag length of twelve months. The other characteristics are the time-series averages of the cross-sectional distress risk average and the number of assets (bonds or stocks) per portfolio. Consistent with Campbell et al.'s (2008) evidence on the stock pricing of distress risk, Table 2 suggests that the mean excess returns and alphas of the value- and equally-weighted bond portfolios decrease with distress risk. Also consistent with Campbell et al. (2008), only the decreases in the alphas but not those in the mean excess returns are, however, statistically significant. For example, Panel A suggests that, while the bond spread portfolio long the top and short the bottom value-weighted distress portfolio has an insignificant mean excess return of –0.09% per month (t-statistic: –0.34), its five-factor alpha is a significant –0.41% (t-statistic: –2.32) and its nine-factor alpha a significant –0.55% (t-statistic: –2.69). The left panel of Figure 1 graphically shows the relations between the mean excess bond returns and alphas and the distress portfolios.

Insert Table 2 here.

More directly corroborating Campbell et al.'s (2008) evidence, Table 2 further shows that the mean excess returns and alphas of the stock portfolios formed using only stocks associated with the bonds also decrease with distress risk. As before, however, only the decreases in the alphas but not those in the mean excess returns are significant. For example, Panel A suggests that, while the stock spread portfolio long the top and short the bottom value-weighted distress portfolio has an insignificant mean excess return of –0.13% (t-statistic: –0.15), its five- and nine-factor alphas are a significant –0.97% (t-statistics: –1.92) and –1.01% (t-statistic: –2.18), respectively. The right panel of Figure 1 graphically shows the relations between the mean excess stock returns and alphas and the distress portfolios.

Figure 2 plots the exposures of the stock and bond distress portfolios on Bai et al.'s (2018) nine

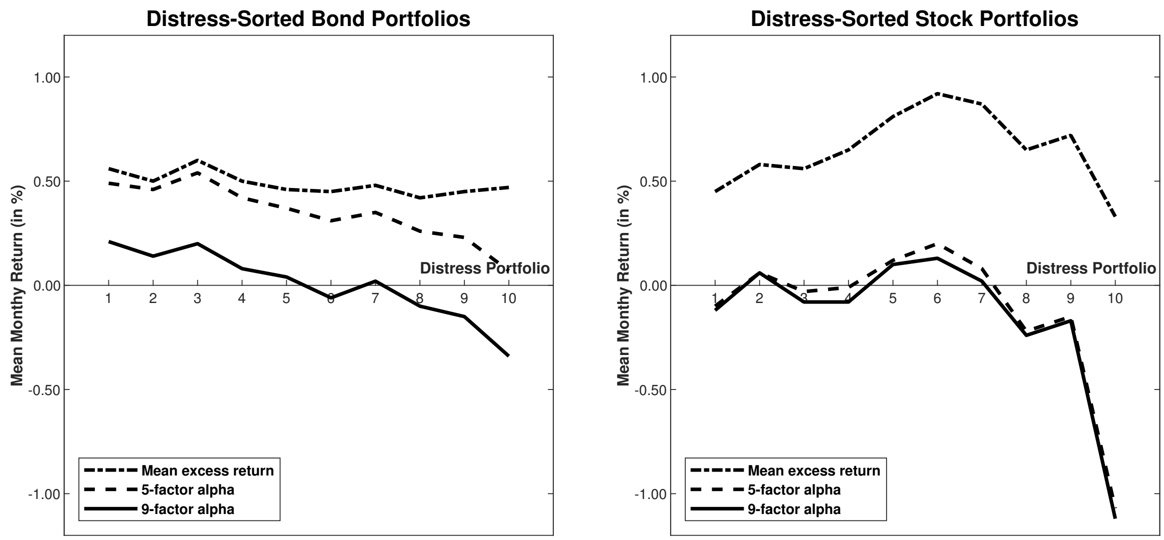

Figure 1: Mean Excess Returns and Alphas of Distress-Sorted Portfolios

This figure plots the mean excess returns and Fama-French five-factor and Bai et al. nine-factor model alphas of the value-weighted distress-sorted bond (left panel) and stock portfolios (right panel) over our sample period.

risk factors, shedding light on why the mean excess returns of the portfolios are so different from their alphas. The figure shows striking trends in the exposures over the portfolios. Starting with the bond portfolios, we see that, of the stock risk factors, the stock market and liquidity exposures increase almost monotonically over the distress portfolios, while the SMB, HML, and stock MOM exposures produce no discernable patterns. Conversely, of the bond market factors, only the bond market exposure but not the bond MOM, DEF, or TERM exposures increase over the distress portfolios. Given that both the stock and the bond market as well as the LIQ factor produce, on average, positive excess returns over our sample period,[11] it is no surprise that the alphas of the bond distress spread portfolios are significantly lower than their mean excess returns. Turning to the stock portfolios, the stock market, HML, and bond market exposures increase almost monotonically over the distress portfolios. Given that the HML factor also produces a positive average return over our sample period, it is also not surprising that the alphas of the stock distress spread portfolios are significantly lower than their mean excess returns.

[11] To be more specific, the average monthly returns of the stock market portfolio, the bond market portfolio, and the liquidity spread portfolio are 0.70%, 0.53%, and 0.24% per month, respectively.

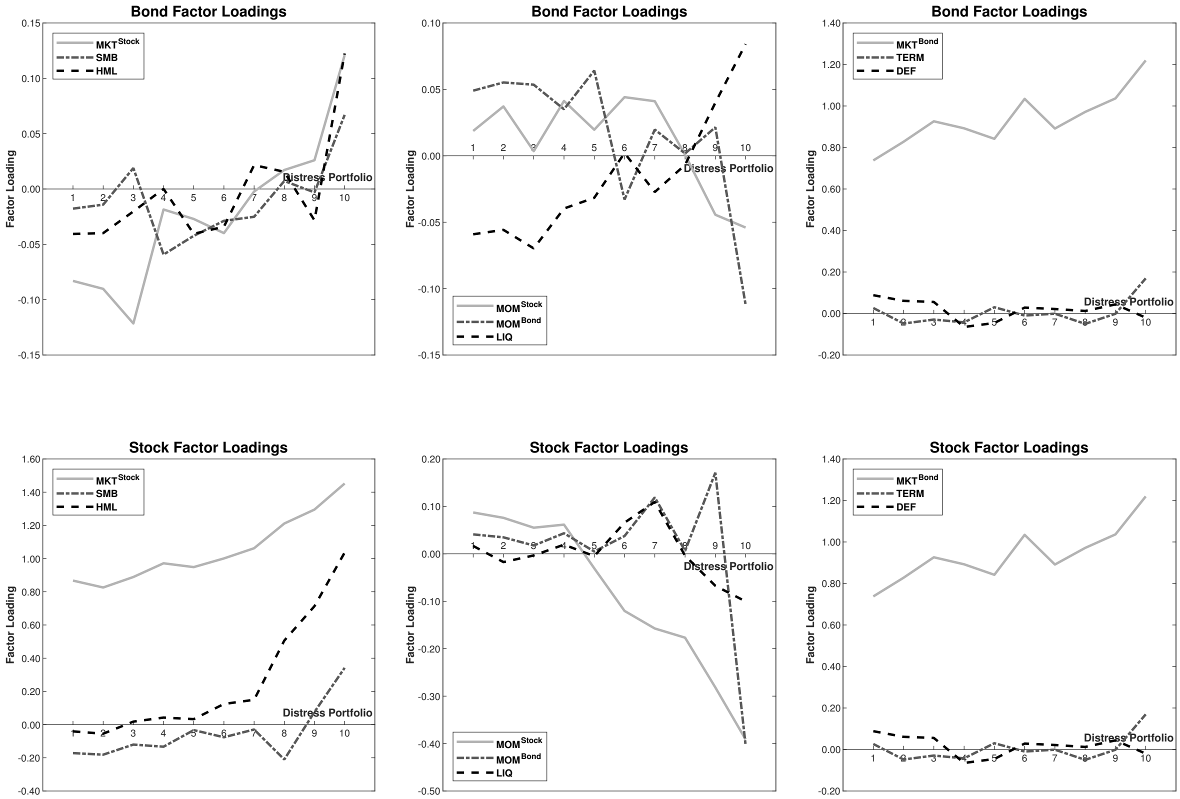

Figure 2: Factor Exposures of Distress-Sorted Bond and Stock Portfolios

This figure plots the factor exposures of the value-weighted distress-sorted bond (upper panels) and stock portfolios (lower panels) over our sample period. We use the nine-factor model to estimate the factor exposures for each portfolio. We show the factor exposures on the factors, $\text{MKT}^{\text{Stock}}$, SMB and HML, in the left panel, the factors ($\text{MOM}^{\text{Stock}}$, MOM^{Bond} and LIQ) in the middle panel and the factors (MKT^{Bond}, TERM and DEF) in the right panel.

3.3 Portfolios Double-Sorted on Firm-Level and Intra-Firm Distress Risk

A potential explanation for the negative relation between firm-level distress risk and corporate bond returns obtained in the previous subsection could be that distressed firms issue higher quality bonds than safer firms. Distressed firms may, for example, grant a higher priority to their bondholders and may issue more secured bonds. To refute that explanation, we now measure the quality of a bond issue using its most recently available credit rating and sort our bond sample into double-sorted portfolios according to their firm- and bond-level distress risk at the end of month $t-1$. As before, we either value- or equally-weight the portfolios and hold them over month t. We adjust for risk by regressing a portfolio's return on Bai et al.'s (2018) nine risk factors and reporting the intercept.

Table 3 presents the results from the double-sorted portfolio formation exercise. In Panel A, we start with sorting our bond sample into four credit rating classes: investment-grade (*Rating*: 1-10), speculative (11-13), highly speculative (14-16), and junk bonds (17-21). Within each class, we sort bonds into quintile portfolios according to their firm-level distress risk. Looking at value- and equally-weighted portfolios in Panels A.1 and A.2, respectively, Panel A suggests that the nine-factor alphas significantly decrease over the distress portfolios within each class. In fact, controlling for a bond's credit rating, the negative distress risk-bond alpha relations become more pronounced, with the alphas of the high-minus-low distress spread portfolios now never attracting a t-statistic above –2.50. Panel B reverses the exercise, first sorting into firm-level distress quintiles and then into the four credit rating classes. Looking at value- and equally-weighted portfolios in Panels B.1 and B.2, respectively, Panel B suggests that, except for the top distress quintile, the nine-factor alphas significantly increase over the credit rating classes within each distress quintile. Most pronouncedly, within the bottom distress quintile, the alphas increase by 0.42% as we move from the value- or equally-weighted investment-grade portfolio to the corresponding junk-bond portfolio (t-statistics about 4.60; see Panels B.1 and B.2).

Insert Table 3 here.

3.4 Asset Portfolios Univariately Sorted on Firm-Level Distress Risk

We finally take a look at the relation between firm-level distress risk and asset returns. Table 4 shows the nine-factor alphas of value- or equally-weighted asset portfolios sorted on firm-level distress risk, with the portfolios being formed using the same procedures as before. The table suggests that the nine-factor alphas of the asset portfolios decrease with distress risk, which is perhaps unsurprising given that both stock and bond returns do so, too. Interestingly, however, the magnitudes of the decreases are slightly smaller than for the stock and bond portfolios, with, for example, the alphas of the high-minus-low distress spread portfolio now only being between –0.22% and –0.38% per month. In accordance, the t-statistics of the spread portfolio alphas are now slightly less significant, with them being around –1.90 except for the book-leverage value-weighted asset return.

Insert Table 4 here.

Overall, we conclude from this section that there is a robust negative relation between firm-level distress risk and the cross-section of corporate bond returns, which becomes statistically significant once we control for popular risk factors. We are able to draw the same conclusions for the subsample of stocks associated with our bond sample. Variations in bond quality across differentially-distressed firms are not responsible for the negative distress risk-bond return relation, but work against it. Controlling for such variations, the negative relation becomes more pronounced and significant. Given the effects of firm-level distress risk on bond and stock returns, we also find a negative relation between firm-level distress risk and asset returns, which are the value-weighted average of stock and bond returns.

4 Does Financial Risk Explain the Bond Distress Premium?

In this section, we study whether financial risk can explain why stock and corporate bond returns decrease with distress risk. Garlappi et al.'s (2008) and Garlappi and Yan's (2011) shareholder advantage theory, for example, suggests that shareholders' ability to extract economic rents from debtholders in distress explains the negative stock distress premium. To see whether that theory can also explain a negative bond distress premium, we first repeat Garlappi et al.'s (2008) simulation exercise to identify the sign of the effect of shareholder advantage on the bond distress premium. We next rerun our asset pricing tests allowing the bond distress premium to depend on popular shareholder advantage proxies.

4.1 Shareholder Advantage and the Pricing of Distressed Debt

4.1.1 A Shareholder Advantage Model of the Firm

In line with Garlappi et al. (2008), we now study whether the shareholder advantage model of Fan and Sundaresan (2000) can explain the distress anomaly in stocks and corporate bonds. Fan and Sundaresan (2000) look at a debt and equity-financed firm operating in continuous time indexed by t. The firm is exposed to a flat corporate tax rate of τ and loses a fraction of firm value α in bankruptcy ("deadweight costs of bankruptcy"). The value of the firm's unlevered assets, V_t, obeys:

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dB_t, \qquad (3)$$

where μ is the expected return on the unlevered assets, $\delta < \mu$ the dividend yield, σ the volatility of the unlevered assets, and dB_t is the increment of a standard Brownian motion.

Turning to the financing side of the model, Fan and Sundaresan (2000) assume that the firm's entire debt takes the form of a single perpetuity with a coupon payment of c per time unit. Since the coupon payment is tax-deductable, it creates a tax shield. Shareholders are able to strategically default on the coupon payment. They use that possibility when the unlevered asset value V_t drops below the threshold level $\tilde{V}_S$ endogenously chosen by them. In default, shareholders and debtholders negotiate about the residual levered firm value, with shareholders ultimately receiving the fraction $\tilde{\theta}$ of residual value and debtholders the fraction $1-\tilde{\theta}$. The fractions are determined by maximizing the joint benefit to shareholders and debtholders in a Nash bargaining game:

$$\tilde{\theta}^* = \text{argmax} \left[\tilde{\theta}\upsilon(V) - 0\right]^{\eta} \left[(1-\tilde{\theta})\upsilon(V) - (1-\alpha)V\right]^{(1-\eta)} = \eta\left(1 - \frac{(1-\alpha)V}{\upsilon(V)}\right), \tag{4}$$

where $\upsilon(V)$ is the levered asset value, and η shareholders' bargaining power. Equation (4) shows that the fraction of firm value allocated to shareholders in default, $\tilde{\theta}$, increases with shareholders' bargaining power, η, and the fraction of firm value lost in bankruptcy, α.

Using standard real options techniques outlined in, for example, Dixit and Pindyck (1994), Fan and Sundaresan (2000) derive closed-form solutions for the levered firm value, $\upsilon(V)$, the equity value, $\tilde{E}(V)$, the debt value, $\tilde{D}(V)$, and the default threshold, $\tilde{V}_S$. Building up on Fan and Sundaresan's (2000) results, Garlappi et al. (2008) derive closed-form solutions for the time-0 expectation of the equity value at time t, $\mathbb{E}_0(\tilde{E}(V_t))$, and the probability that the unlevered asset value V_t hits the threshold $\tilde{V}_S$ over the period from time 0 to T, $\text{Prob}_{(0,T]}(V_0)$ ("strategic default probability"). Using the equity value expectation, they calculate the expected equity return, defined as the ratio of the expected equity value to its current value. We show the closed-form solutions derived by Fan and Sundaresan (2000) and Garlappi et al. (2008) in Appendix A. In the same appendix, we also derive the time-0 expectation of the debt value at time t, $\mathbb{E}_0(\tilde{D}(V_t))$, which, since $\tilde{D}(V) = \upsilon(V) - \tilde{E}(V)$, only requires us to derive the time-0 expectation of the levered asset value, $\mathbb{E}_0(\upsilon(V_t))$. Using the expected levered asset value and the expected debt value, we calculate the expected levered asset return and the expected debt return over and above the expected equity return.

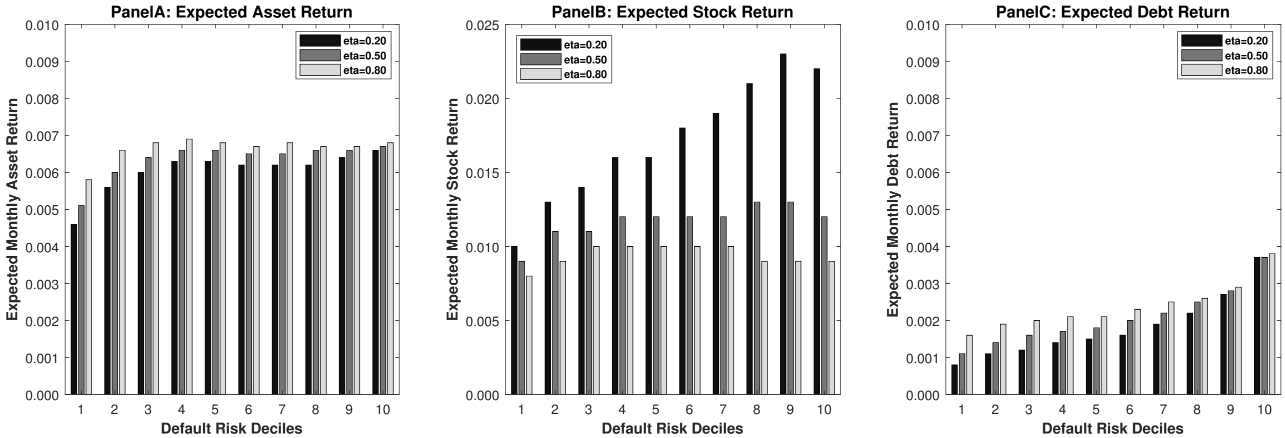

Figure 3: Shareholder Advantage and Expected Asset, Stock, and Debt Returns

The figure shows the monthly expected levered asset returns (Panel A), stock returns (Panel B), and debt returns (Panel C) of decile portfolios sorted according to strategic default risk in the shareholder advantage model of Fan and Sundaresan (2000) with a shareholder bargaining power (eta) of either 0.20, 0.50, or 0.80. We describe the simulations and analytical formulas used to create the figure in Section 4.1 and Appendix A, respectively.

4.1.2 Simulation Results

We use the closed-form solutions derived in Section 4.1.1 to extend the simulation exercise of Garlappi et al. (2008). In line with them, we calculate expected returns over a one-month horizon and default risk over a one-year horizon, and we set the risk-free rate, r, to 0.04, the payout rate, δ, to 0.04, the tax rate, τ, to 0.35 and the bankruptcy costs, α, to 0.50. Also in line with them, we draw the coupon rate, c, the expected unlevered asset return, μ, and the initial unlevered asset value, V_0, from uniform distributions with support $[0.05, 0.10]$, $[\delta + \frac{1}{2}\sigma, 3(\delta + \frac{1}{2}\sigma)]$, and $[V_S, V_S + 1.25]$, respectively. Since we do not have access to the asset volatility estimates from Moody's KMV Corporation, we also draw these from a uniform distribution with support $[0.10, 0.30]$. Relying on a shareholder bargaining power η of 0.20, 0.50, or 0.80, we simulate 100,000 firms and calculate their expected levered asset returns, expected equity returns, expected debt returns, and default risk using the formulas in Appendix A. We next sort the firms into ten decile portfolios according to their distress risk. We finally compute the equally-weighted expected levered asset-, equity-, and debt-returns of the portfolios.

Figure 3 plots the results from the simulations, with Panels A, B, and C focusing on the expected levered asset, equity, and debt return, respectively. Panel B corroborates Garlappi et al.'s (2008) result that a higher shareholder bargaining power, η, can turn the default risk-expected equity return relation from being almost monotonically positive to hump-shaped, with high default risk firms having a (marginally) lower expected equity return than low default risk firms. Conversely, consistent with the intuition that debtholders hold a zero-risk long perpetuity and a high-risk short put option entitling shareholders to default on their debt payments, and that the short option's risk increases with default risk, Panel C shows that the default risk-expected debt return relation is consistently positive in all our simulations. Perhaps surprisingly, the panel, however, also suggests that the relation does not become more but less positive with a higher shareholder bargaining power. Panel A hints at the reason, with it suggesting that the negative effect of shareholder bargaining power on the default risk-expected debt return relation stems from a similarly negative effect of shareholder bargaining power on the default risk-expected levered asset return relation. Notwithstanding, the most important takeaway is that, under realistic model input parameters, the Fan and Sundaresan (2000) shareholder advantage model produces a consistently positive default risk-expected debt return relation.

4.2 Conditioning the Bond Distress Premium on Shareholder Advantage

Section 4.1 presents theoretical evidence that shareholder advantage theories are unable to explain a negative distress premium in corporate debt including bonds. To further substantiate that evidence, we next condition the bond distress premium estimate obtained in Section 3 on popular shareholder advantage proxies, including a firm's R&D intensity, its industry concentration, and its asset tangibility. Opler and Titman (1994) show that highly levered firms with a high R&D intensity often encounter cash flow problems in recessions, triggering their cash-flow-related covenants and preventing them from renegotiating their debt. Conversely, Shleifer and Vishny (1992) and Acharya et al. (2011) show that firms operating in concentrated industries and mostly owning intangible assets are often forced to sell their assets at fire-sale discounts in distress, making debtholders more willing to compromise to avoid a liquidation. Thus, the literature usually interprets a lower R&D intensity, a higher industry concentration, and a lower asset tangibility as signalling greater shareholder advantage.

We calculate a firm's R&D intensity as the ratio of its R&D expenses to its total assets. In accordance with Garlappi et al. (2008), we employ the sales-based Herfindahl index to measure an industry's concentration. We calculate that Herfindahl index for industry j as:

$$Herfindahl_j = \sum_{i=1}^{I_j} s_{i,j}^2,$$

where $s_{i,j}$ is the fraction of firm i's sales over the total sales of FF49 industry j, and I_j is the number of firms belonging to that industry. We calculate a firm's asset tangibility as the ratio of its gross property, plant and equipment (PPE) to its total assets. We take all accounting variables required to calculate the shareholder advantage proxies from the fiscal-year end in calendar year $t-1$. We use the proxies from July of calendar year t to June of calendar year $t+1$.

We start with using portfolio sorts to gauge the effect of the shareholder advantage proxies on the distress premium in corporate bonds. To do so, we sort our bond sample (alternatively, the associated stock sample) into portfolios according to the tercile breakpoints of each shareholder advantage proxy at the end of month $t-1$. Within each shareholder advantage portfolio, we next sort the same assets into portfolios according to the quintile breakpoints of firm-level distress risk at the end of month $t-1$, giving us portfolios double-sorted on each shareholder advantage proxy and distress risk.[12] We either value- or equally-weight the double-sorted portfolios and hold them over month t, adjusting for risk by regressing each portfolio's return on the nine Bai et al. (2018) risk factors.

Table 5 presents the nine-factor alphas of the bond and stock portfolios double-sorted on shareholder advantage and distress risk. In Panels A to C, we use R&D intensity, the Herfindahl index, and asset tangibility to proxy for shareholder advantage, respectively. In each panel, the column titled "Strong (Weak) Shareholder Power" shows the alphas of those portfolios containing the 33% of firms with the highest (lowest) shareholder advantage according to the proxy used in the panel. Remarkably, the table suggests that, despite them being almost always significant, the declines in the bond alphas over the distress portfolios are virtually unrelated to shareholder advantage. Using asset tangibility to measure shareholder advantage, Panel C, for example, suggests that the decline in the value-weighted bond alpha is 0.31% (t-statistic: –2.48) for strong shareholder advantage firms and 0.48% (t-statistic: –2.38) for weak shareholder advantage firms. Looking at either value- or equally-weighted portfolios, the two other proxies, R&D intensity and the Herfindahl index, yield similarly narrow differences in the bond alpha declines over the set of distress portfolios (see Panels A and B).

Insert Table 5 here.

Turning to the stock portfolios, the situation changes dramatically. Supporting Garlappi et al.

[12] We only sort into two median portfolios in case of R&D intensity. We do so since, when following other studies and setting missing R&D expenditures equal to zero, more than half of all firms have zero R&D expenditures, making it impossible to sort into more granular (e.g., decile or quintile) portfolios.

(2008), we find that the stock alpha declines over the distress portfolios are far more pronounced for strong than weak shareholder advantage firms. Using the Herfindahl index to measure shareholder advantage, Panel B, for example, suggests that the decline in the value-weighted stock alpha is 0.62% (t-statistic: –2.05) for strong and 0.08% (t-statistic: –0.26) for weak shareholder advantage firms. Using the two other two shareholder advantage proxies, we find similarly large differences between the two types of firms (see Panels A and C). Notwithstanding, presumably due to the fact that we study a relatively narrow cross-section of stocks, the stock alpha declines are often insignificant.

We next also run FM regressions of bond (alternatively, stock) returns over month t on combinations of firm-level distress risk, the shareholder advantage proxies, interactions between firm-level distress risk and the shareholder advantage proxies, and controls measured at the end of month $t-1$. To mitigate that the firm-level distress risk proxy is heavily right-skewed, we take its natural log before entering it into the regressions. Also, instead of directly including the shareholder advantage proxies in the regressions, we rely on dummy variables signalling that shareholder advantage is high according to either shareholder advantage proxy. *LowR&D* is a dummy variable equal to one if a firm's R&D intensity is below the third quartile in a month, else zero; *HighHSI* is a dummy variable equal to one if a firm operates in an industry with a Herfindahl index value above the median, else zero; and *LowTangibibility* is a dummy variable equal to one if a firm's asset tangibility is below the median in a month, else zero. Table 6 reports the results from the regressions, with Panel A focusing on the bond return regressions and Panel B on the stock return regressions. Plain numbers are monthly risk premium estimates (in percent), while the numbers in square parentheses are t-statistics calculated from Newey and West (1987) standard errors with a lag length of twelve months.

Insert Table 6 here.

Starting with the bond regressions in Panel A, model (1) suggests that, using only distress risk and the controls as exogenous variables, distress risk earns a significantly negative premium of –26 basis points per month (t-statistic: –3.23). Allowing the shareholder advantage proxies to independently or jointly condition the negative distress premium, models (2) to (9) suggest that neither does so, with no interaction term attracting an absolute t-statistic larger than 1.25. Turning to the stock regressions in Panel B, model (1) suggests that using only distress risk and the controls as exogenous variables produces a negative albeit insignificant relation between distress risk and stock returns (t-statistic:

–0.48). More importantly, models (2) to (9) show that two shareholder advantage proxies suggest that high shareholder advantage produces a significantly more negative distress risk-stock return relation, consistent with Garlappi et al. (2008). In particular, model (3) shows that a low R&D intensity leads the stock distress premium to decline by 30 basis points (t-statistic: –2.36), while model (5) shows that operating in a high Herfindahl index industry lowers it by 25 basis points (t-statistic: –2.11). In contrast, model (7) shows that a low asset tangibility does not affect the stock distress premium.

Overall, this section offers evidence that popular shareholder advantage proxies do not condition the bond distress premium obtained in Section 3, despite them continuing to condition the same premium in stocks even in our narrow cross-section and short sample period. Thus, shareholder advantage does not offer a consistent explanation for the distress premia in stocks and corporate bonds.

5 Does Asset Risk Explain the Bond Distress Premium?

In this section, we ask whether real options models of the firm are more successful in explaining why stock and corporate bond returns decrease with distress risk. Assuming investments are only partially reversible, the models suggest that *economically* unprofitable firms are close to exercising their disinvestment options, lowering their expected asset returns. Yet, if economic and financial distress change in tandem, disinvestment options may also lead expected stock and debt returns to decline with financial distress. We first study that possibility within a real options model in which the firm can gradually disinvest capacity. The model is standard except for allowing the firm to be equity- *and* debt-financed. We next rerun our asset pricing tests allowing the stock and bond distress premiums to depend on disinvestment proxies.

5.1 The Pricing of Distressed Debt Under Disinvestment

5.1.1 A Real Options Model of the Firm Allowing for Disinvestment

We study a modified version of the standard real options model of Aretz and Pope (2018), who extend Pindyck's (1988) model to allow for the gradual disinvestment of productive capacity. In the model, a monopolistic firm operating in continuous time indexed by t optimally makes capacity and production decisions to maximize profits from producing and instantaneously selling some quantity of a homogenous output good. The firm has an initial productive capacity of $\bar{K}$. Each capacity unit allows the firm to produce and sell one unit of output per time unit, so that quantity, Q, is within $\{0; \bar{K}\}$. Each output unit is sold at a stochastic price, θ, evolving according to the differential equation:

$$d\theta = (\mu - \delta)\theta dt + \sigma\theta dW, \tag{5}$$

where μ is the total expected return, δ the dividend yield, and σ the volatility of the return of a traded asset replicating the variations in price, and W is a Brownian motion. The variable costs of producing Q units of output, $C(Q)$, are: $c_1 Q + \frac{1}{2}c_2 Q^2$, while the fixed costs, $F(\bar{K})$ are: $f\bar{K}$, where $c_1 \geq 0$, $c_2 \geq 0$, and $f \geq 0$ are parameters. The firm's total profits per time unit, $\pi(Q)$, are then:

$$\pi(Q) = \theta Q - c_1 Q - \frac{1}{2}c_2 Q^2 - f\bar{K}, \tag{6}$$

implying that the firm maximizes profits by choosing $Q = \min(\frac{\theta - c_1}{c_2}; \bar{K})$ in each instant. Finally, the firm is able to sell off productive capacity for a unit price equal to $s \geq 0$. In comparison to Aretz and Pope (2018), the only differences between our model and theirs is that (i) we do not allow the firm to expand its productive capacity, and (ii) we include fixed production costs $F(\bar{K})$. In Appendix B, we show how to derive the firm's optimal disinvestment policy and how to value the firm.

Turning to the financing side of the model, we assume that the firm's entire debt takes the form of one single zero-coupon bond with a contractual payment of C and a maturity time of T. If the value available to debtholders exceeds C at time T, shareholders pay off debtholders, and the firm continues to exist. If it does not, the firm defaults and is liquidated. To satisfy their claims, debtholders have full recourse to the firm's productive assets at time T, but not past profits, which the firm instantaneously distributes to shareholders as dividends. In addition, although the firm also instantaneously distributes disinvestment proceeds to shareholders, debtholders are able to reclaim these proceeds in default if they fall within a "suspect period" (a legally-defined period preceding the default time; see Wood (2007, Chapter 17)). Using risk-neutral pricing, the value of debt, $D(\theta, C)$, is then:

$$D(\theta, C) = E^{\mathbb{Q}}\left[e^{-r(T-t)} \min(C, V(\theta(T), \bar{K}(T)) + S)\right], \tag{7}$$

where $E^{\mathbb{Q}}$ is the risk-neutral expectation, r the risk-free rate, $V(\theta(T), \bar{K}(T))$ the value of the remaining productive capacity at time T, and S the compounded-up value of the disinvestment proceeds that fell within the suspect period. Conversely, Cox and Rubinstein (1985) show that the instantaneous expected debt return is $\frac{\partial D(\theta,C)}{\partial \theta} \times \frac{\theta}{D(\theta,C)}$ multiplied by the expected excess return of the asset replicating variations in the price θ. Given that there is no closed-form solution for the expectation in Equation (7), we use Monte Carlo simulations to find the value and expected return of the debt claim.

We also calculate the equity value using a discounted risk-neutral expectation. Having done so, we again use Cox and Rubinstein's (1985) formula to derive the expected equity return.

5.1.2 Monte Carlo Simulation Results

We use Monte Carlo simulations to find out whether the real options model can produce negative relations between distress risk and both expected stock and debt returns, using 100,000 iterations for each set of parameters. We assume that the firm starts with an initial capacity, $\bar{K}$, of 1.00. Also, we set the total expected return, μ, the dividend yield, δ, and the volatility, σ, of the price replication asset equal to 16%, 4%, and 30%, respectively, while we set the production cost parameters, c_1, c_2, and f, equal to 0.00, 0.30, and 0.20, respectively. The zero-coupon bond has a contractual payment, C, of 10 and a maturity time, T, of 2.00. To vary the attractiveness of disinvestment, we set the disinvestment price, s, to 0.00, 4.00, or 8.00. We assume that shareholders capture disinvestment proceeds over the first year, but debtholders over the second. To vary the firm's economic (and also financial) health, we choose an initial price, θ, between 0.45 and 2.50, where 0.45 is slightly above the level below which the firm would instantaneously start disinvesting when the disinvestment price is at its highest value ($s = 8.00$).

Figure 4 plots the results from the simulation exercise, with Panels A, B, and C displaying the expected asset, equity, and debt return, respectively. Panel A suggests that the expected asset return increases (decreases) with the firm's economic health when the disinvestment price is low (high), in line with Aretz and Pope's (2018) main conclusions. The intuition is that when firms have disinvestment options and are close to exercising them, disinvestment options reduce asset risks and produce lower expected asset returns. Panels B and C reveal that disinvestment options also reduce the expected stock and debt returns of economically distressed firms since the benefits from disinvestment can accrue to both shareholders and debtholders. Taken together, the real options model thus confirms that disinvestment options can explain why both stock and bond returns decrease with distress risk.

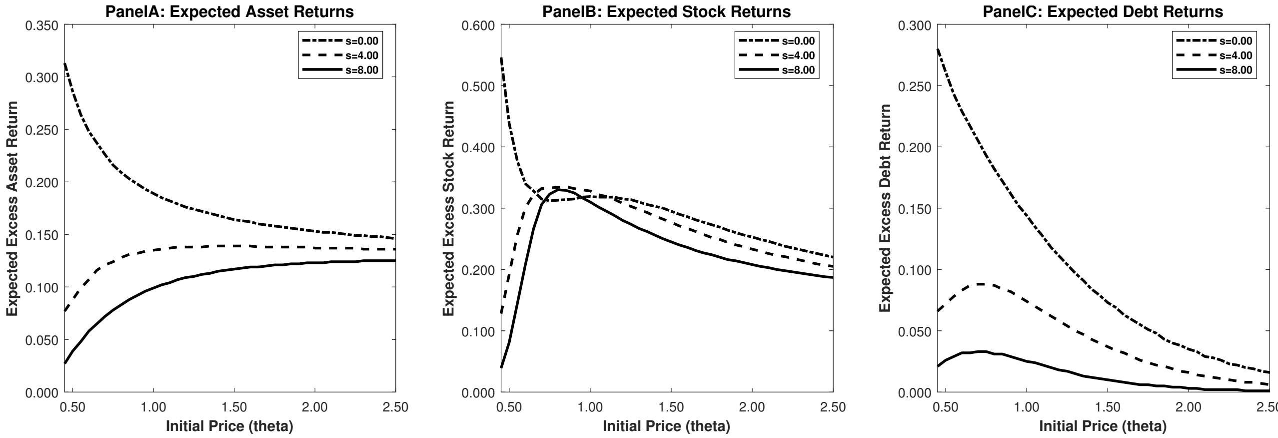

Figure 4: Disinvestment Option and Expected Asset, Stock, and Debt Returns

The figure shows the expected asset returns (Panel A), stock returns (Panel B), and debt returns (Panel C) over differenct economic health conditions of firms in a modified version of the standard real options model of Aretz and Pope (2018) with a disinvestment attractiveness (s) of either 0.00, 4.00, or 8.00. We describe the simulations and analytical formulas used to create the figure in Section 5.1 and Appendix B, respectively.

5.2 Conditioning the Bond Distress Premium on Disinvestment Options

Section 5.1 offers theoretical evidence that disinvestment options may be behind the negative relations between distress risk and both stock and corporate bond returns. To empirically test that possibility, we condition the stock and bond distress premia obtained in Section 3 on two disinvestment option value proxies, gross profitability and the extent to which a firm's installed capacity exceeds its optimal capacity ("capacity overhang"). A low gross profitability and high capacity overhang signal that a firm is economically unprofitable, suggesting that its disinvestment options are deep in-the-money. In line with Novy-Marx (2013), we calculate a firm's gross profitability as the ratio of the difference between its sales and costs of good sold ("gross profits") to its total assets. We take the values of the accounting variables from the fiscal year ending in calendar year $t-1$ and use the calculated ratio from July of calendar year t to June of calendar year $t+1$. In line with Aretz and Pope (2018), we use a recursively estimated stochastic frontier model to measure capacity overhang. The stochastic frontier model decomposes a firm's installed capacity into the sum of an optimal capacity estimate and a positively-signed capacity overhang residual. Installed capacity is proxied for using the log of the sum of PPE and long-term intangibles. Conversely, optimal capacity is a linear function of optimal capacity determinants (as, e.g., log sales, log costs of goods sold, and stock volatility) and a normally-distributed mean-zero error term. Finally, the capacity overhang residual is a normally-distributed error term truncated from below at zero. Crucially, the expectation of that residual is a linear function of capacity overhang determinants (as, e.g., the percent decline in sales over some past period if positive, else zero). We provide more details about the capacity overhang variable in Appendix B.

We again start with portfolio sorts to estimate the conditioning effect of disinvestment option value on the bond and stock distress premia. To do so, we sort our bond sample (alternatively, the associated stock sample) into portfolios according to the tercile breakpoints of each disinvestment value proxy at the end of month $t-1$. Within each disinvestment value portfolio, we next sort the same assets into portfolios according to the quintile breakpoints of firm-level distress risk at the end of month $t-1$, giving us portfolios double-sorted on disinvestment value and distress risk. As before, we either value- or equally-weight the portfolios and hold them over month t. We form a high-minus-low distress spread portfolio within each disinvestment value portfolio, once again adjusting the spread portfolio for risk by regressing its return on the nine Bai et al. (2018) factors.

Table 7 presents the nine-factor alphas of the bond and stock portfolios double-sorted on disinvestment value and distress risk, with Panel A using gross profitability and Panel B capacity overhang to measure disinvestment value. In each panel, the column titled "High (Low) Disinvestment Value" shows the alphas of those portfolios containing the 33% of firms with the highest (lowest) disinvestment values according to the proxy used in the panel. Starting with the bond portfolios, we see that a higher disinvestment value predicts a more negative distress risk-bond return relation. For example, Panel A suggests that, while the value-weighted bond distress spread portfolio has a mean monthly return of –0.24% (t-statistic: –2.65) for high gross-profitability (i.e., low disinvestment value) stocks, the same portfolio attracts a more than double mean return of –0.57% (t-statistic: –2.55) for low gross-profitability (i.e., high disinvestment value) stocks. In the same vein, Panel B suggests that the mean return of that spread portfolio is –0.25% (t-statistic: –3.04) for low capacity overhang (i.e., low disinvestment value) stocks, but a much higher –0.42% (t-statistic: –2.38) for high capacity overhang (i.e., high disinvestment value) stocks.

Insert Table 7 here.

Importantly, the table shows that the conditioning effect of disinvestment value on the distress risk-stock return relation is also negative in three out of four cases. For example, Panel A suggests that, while the equally-weighted stock distress spread portfolio has a mean monthly return of 0.17%

(t-statistic: 0.78) for high gross-profitability (i.e., low disinvestment value) stocks, the same portfolio attracts a much lower mean return of –0.10% (t-statistic: –0.33) for low gross-profitability (i.e., high disinvestment value) stocks. However, presumably again due to us studying a narrow cross-section of stocks over a short sample period, the stock spread portfolios never attract a significant alpha for either the high or low disinvestment value stocks (most negative t-statistic: –1.10).

Table 8 presents the results from FM regressions of bond (Panel A) or stock (Panel B) returns over month t on combinations of distress risk, the disinvestment value proxies, interactions between these variables, and control variables at the end of month $t-1$. Running the FM regressions, we are able to test for the significance of the conditioning effect of disinvestment value on the bond or stock distress premium. To alleviate skewness and kurtosis effects, we take the log of distress risk and the disinvestment value proxies before entering them into the regressions. As before, instead of directly including the disinvestment value proxies in the regressions, we again rely on dummy variables signalling that a firm is close to exercising its disinvestment options according to either proxy. *LowGrossProfits* is a dummy variable equal to one if a firm's gross profitability is below the median, else zero; and *HighOverhang* is a dummy variable equal to one if a firm's capacity overhang is above the median, else zero. The control variables are exactly the same as those also used in Table 6.

Starting with the bond regressions, Panel A suggests that a higher disinvestment value significantly decreases the distress risk-bond return relation. Using either disinvestment value proxy, columns (3) and (5), for example, show that a lower gross profitability (signalling a higher disinvestment value) decreases the bond distress premium by 0.27% per month (t-statistic: –2.08), while a higher capacity overhang (also signalling a higher value) decreases that premium by 0.17% (t-statistic: –1.98). Jointly using the disinvestment value proxies, column (6) suggests that only gross profitability, but not capacity overhang, significantly conditions the distress premium in bonds.

Insert Table 8 here.

Turning to the stock regressions, Panel B suggests that gross profitability, but not capacity overhang, also significantly conditions the distress risk-stock return relation with the anticipated sign in the model featuring both disinvestment value proxies (see column (6)). However, likely as a result of the limited sample size in these tests, the other conditioning effects fail to attract significance.

Overall, our empirical findings in this section suggest that low gross profitability or high capacity overhang, both signalling valuable disinvestment options, can go some way toward explaining the negative distress risk-bond return relation, as suggested by real options models of the firm. Alas, the same variables lack power to explain the distress risk-stock return relation in the subsample of stocks associated with our bond sample. In the next section, we thus study the variables' ability to explain that relation in a more comprehensive cross-section of stocks over a longer sample period.

6 Robustness Test

Since our idea to explain the negative relations between distress risk and the cross-sections of stock and corporate bond returns using disinvestment options is new to the literature, it is somewhat unnatural to immediately test that idea on the subsample of stocks of firms that also have bonds outstanding. To remedy that problem, we next estimate the conditioning effect of disinvestment options on the distress risk-stock return relation using a more comprehensive cross-section of stocks over a longer sample period. In particular, we now consider the entire cross-section of CRSP common stocks traded on the NYSE, AMEX, and Nasdaq over the 1981 to 2017 sample period.[13] In line with other studies, we exclude financial (SIC code: 6000-6999) and utility stocks (4900-4949). To alleviate market microstructure biases, we further exclude stocks with a one-month-lagged market capitalization in the bottom quartile from both the equally-weighted portfolios and the FM regressions (see Hou et al. (2016)).

Table 9 presents the mean returns, alphas, and characteristics of value-weighted (Panel A) and equally-weighted distress risk portfolios (Panel B) formed using the same conventions as in Table 2, but featuring the more comprehensive cross-section of stocks over the longer sample period. Corroborating the evidence of Campbell et al. (2008), the main message of the table is that the more comprehensive data also produces a distress anomaly, which typically becomes significant when we control for the Fama-French (1993) three factors or the Bai et al. (2019) nine factors. More importantly, Table 10 shows the results from repeating the FM regressions conditioning the distress risk-stock return relation on the disinvestment proxies (gross profitability and capacity overhang) in Table 8 using the more comprehensive data. The table shows that a lower gross profitability (signalling a higher disinvestment value) yields a significantly more negative stock distress premium (see columns (3) and (6)), while it

[13]The starting point of the longer sample period is dictated by the availability of the distress risk proxy.

does not suggest that capacity overhang significantly conditions that premium.

Insert Table 9 here.

Insert Table 10 here.

In sum, the stock pricing tests conducted on the more comprehensive sample over the longer sample period thus offer some more evidence that operating profitability significantly conditions the distress risk-stock return relation, but, unfortunately, not that capacity overhang does the same.

7 Conclusion

We offer empirical evidence suggesting a negative relation between firm-level distress risk and the cross-section of corporate bond returns, similar to the often negative relation between distress risk and stock returns obtained in prior studies. The negative distress risk-bond return relation becomes economically larger and statistically significant when controlling for popular stock and bond pricing factors, shows up in both value- and equally-weighted portfolio sorts and FM regressions, and is not attributable to distressed firms issuing higher-quality bonds than safer firms. Combining stock and bond returns to calculate a proxy for the asset return, we further offer evidence that distress risk is also negatively, albeit less significantly so, related to the cross-section of asset returns.

Our findings have important implications for the literature. In particular, they are first in casting some doubt on shareholder advantage explaining the distress anomaly, in particular, and shareholder advantage theories, in general. They do so since, as we show, shareholder advantage theories are unable to produce a negative relation between distress risk and debt returns. Consistent with that observation, popular shareholder advantage proxies fail to condition the bond distress premium estimate in our empirical work. We finally show that real options asset pricing models are more promising to explain why both stock and bond returns decrease with distress risk. These models predict that disinvestment options can lead asset returns to decrease with distress risk, with the low asset returns likely dragging down stock and bond returns, too. Supporting these models, disinvestment value proxies have some ability to condition the relations between distress risk and both stock and bond returns.

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Table 1: Descriptive Statistics

In this table, we present descriptive statistics for our analysis variables. Panel A reports the number of bond-month observations, the cross-sectional mean, median, standard deviation, and selected percentiles of the monthly corporate bond return, and bond characteristics including the most recent credit rating, the years-until-maturity, and the market size (in billions). The credit rating is an integer between one and 21, with one referring to a triple A rating and 21 to a C rating. Panel B reports the number of stock-month observations, the cross-sectional mean, median, standard deviation and selected percentiles of the monthly stock return, and stock characteristics including market size (in billions). Panel C reports firm characteristics. Distress risk is the probability that the firm fails over the coming twelve months, calculated using the methodology of Campbell et al. (2008). Book leverage is the ratio of book assets to book equity, and market leverage is the ratio of book assets to market equity. Asset size is the book value of the firm's total assets, measured in billions. The sample period is from July 2002 to June 2017.

			Standard	Percentiles						
	Obs	Mean	Deviation	1	5	25	50	75	95	99
Panel A: Bond Characteristics										
Return (%)	556,965	0.62	4.48	–9.51	–3.68	–0.51	0.44	1.69	5.13	11.39
Credit Rating	556,965	7.49	3.49	1.00	1.00	5.00	7.00	9.50	14.50	16.00
Time-to-Maturity (years)	556,965	9.63	8.82	1.17	1.62	3.72	6.55	11.13	27.97	29.93
Market Size (in billions)	556,965	0.57	0.61	0.00	0.01	0.25	0.40	0.75	1.75	3.00
Panel B: Stock Characteristics										
Return (%)	556,965	0.96	10.21	–27.05	–13.15	–3.49	0.96	5.31	14.33	28.45
Market Size (in billions)	556,965	58.60	82.70	0.23	1.12	7.34	21.60	70.20	240.00	364.00
Panel C: Firm Characteristics										
Distress Risk (%)	556,965	0.09	0.32	0.01	0.01	0.03	0.04	0.06	0.21	1.14
Book Leverage	556,965	6.71	26.11	1.41	1.66	2.26	3.19	6.92	16.12	32.24
Market Leverage	556,965	4.23	6.51	0.28	0.49	1.11	1.94	4.00	17.07	32.25
Asset Size (in billions)	556,965	255.22	523.35	0.70	2.41	12.94	39.12	178.35	1787.63	2265.79

Table 2: Bond and Stock Portfolios Univariately Sorted on Firm-Level Distress Risk

In this table, we present the mean excess returns and alphas of bond and stock portfolios univariately sorted on firm-level distress risk. We form the portfolios by sorting either bonds or stocks into portfolios according to the decile breakpoints of our firm-level distress risk proxy at the end of month $t-1$. The firm-level distress risk proxy is Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. We either value- (Panel A) or equally-weight the portfolios (Panel B) and hold them over month t. We calculate the bond weights using notional bond values outstanding and the stock weights using market equity values. We also form a spread portfolio long the highest distress risk decile and short the lowest ("High–Low"). The table reports the time-series average of the cross-sectional averages of distress risk, the average numbers of bonds/stocks per portfolio, and the average excess bond/stock returns, Fama-French five-factor alphas and Bai et al. (2019) nine-factor alphas for each bond/stock portfolio. Average distress risk, the average excess returns, and the alphas are in monthly percentage terms. We obtain the alphas from regressing a portfolio's return on the relevant factors and reporting the intercept from that regression. The five-factor model factors are the excess stock market return ($\text{MKT}^{\text{Stock}}$), the size factor (SMB), the value factor (HML), the term factor (TERM) and the default factor (DEF). The nine-factor model adds to these the stock momentum factor ($\text{MOM}^{\text{Stock}}$), the stock liquidity risk factor (LIQ), the bond market factor (MKT^{Bond}) and the bond momentum factor (MOM^{Bond}). Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are given in parentheses.

	Bonds					Stocks				
Decile	Mean Dist. Risk	Mean # Bonds	Mean Return	FF5 Alpha	B9 Alpha	Mean Dist. Risk	Mean # Stocks	Mean Return	FF5 Alpha	B9 Alpha
Panel A: Value-Weighted Distress Risk Portfolios										
1 (L)	0.01	377	0.56	0.49	0.21	0.01	71	0.45	–0.10	–0.12
2	0.02	384	0.50	0.46	0.14	0.02	71	0.58	0.06	0.06
3	0.03	382	0.60	0.54	0.20	0.03	71	0.56	–0.03	–0.08
4	0.03	382	0.50	0.42	0.08	0.03	71	0.65	–0.01	–0.08
5	0.04	383	0.46	0.37	0.04	0.04	71	0.81	0.12	0.10
6	0.05	382	0.45	0.31	–0.06	0.05	71	0.92	0.20	0.13
7	0.07	387	0.48	0.35	0.02	0.06	71	0.87	0.08	0.02
8	0.09	382	0.42	0.26	–0.10	0.09	71	0.65	–0.22	–0.24
9	0.14	388	0.45	0.23	–0.15	0.15	71	0.72	–0.15	–0.17
10 (H)	0.51	408	0.47	0.07	–0.34	0.76	72	0.33	–1.07	–1.12
H–L			–0.09	–0.41	–0.55			–0.13	–0.97	–1.01
t-stat.			[–0.34]	[–2.32]	[–2.69]			[–0.15]	[–1.92]	[–2.18]
Panel B: Equally-Weighted Distress Risk Portfolios										
1 (L)	0.01	377	0.58	0.51	0.26	0.01	71	0.73	0.11	0.05
2	0.02	384	0.53	0.48	0.19	0.02	71	0.75	0.13	0.07
3	0.03	382	0.64	0.58	0.27	0.03	71	0.80	0.12	0.05
4	0.03	382	0.57	0.50	0.17	0.03	71	0.89	0.16	0.05
5	0.04	383	0.48	0.40	0.12	0.04	71	1.10	0.31	0.19
6	0.05	382	0.52	0.40	0.01	0.05	71	1.17	0.35	0.26
7	0.07	387	0.52	0.39	0.09	0.06	71	1.00	0.11	–0.02
8	0.09	382	0.49	0.30	–0.12	0.09	71	1.07	0.03	–0.03
9	0.14	388	0.52	0.30	–0.11	0.15	71	1.08	–0.03	–0.20
10 (H)	0.51	408	0.52	0.10	–0.35	0.76	72	1.01	–0.57	–0.72
H–L			–0.05	–0.41	–0.62			0.28	–0.68	–0.77
t-stat.			[–0.17]	[–2.07]	[–2.72]			[0.30]	[–1.09]	[–1.81]

Table 3: Bond Portfolios Double-Sorted on Firm- and Bond-Distress Risk

In this table, we present the nine-factor model alphas of bond portfolios double-sorted on firm- and bond-level distress risk. In Panel A, we form the portfolios by sorting bonds into portfolios according to their most recent credit rating at the end of month $t-1$. Within each credit rating portfolio, we then sort into portfolios according to the quintile breakpoints of our firm-level distress risk proxy at the same time. In Panel B, we reverse the exercise, first sorting into quintile firm-level distress risk portfolios and then into credit-rating portfolios. The firm-level distress risk proxy is Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. The credit rating is an integer between one and 21, with one referring to a triple A rating and 21 to a C rating. Investment grade bonds have numbers from 1 to 10, speculative bonds from 11 to 13, highly speculative bonds from 14 to 16, and junk bonds from 17 to 21. We either value- (Panels A.1 and B.1) or equally-weight the portfolios (Panels A.2 and B.2) and hold them over month t. We calculate the bond weights using notional bond values outstanding and the stock weights using market equity values. Within each first-sorting-variable portfolio, we form a spread portfolio long the highest second-sorting-variable portfolio and short the lowest ("High–Low"). The table shows the average number of bonds per portfolio and the Bai et al. (2018) nine-factor alpha, in monthly percentage terms. See the caption of Table 2 for details on how we calculate the nine-factor model alpha. Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are in parentheses.

Panel A: First Sorting Variable: Credit Rating; Second: Distress Risk								
	Credit Rating							
	Investment Grade		Speculative		Highly Speculative		Junk	
Distress Risk	Obs	Alpha	Obs	Alpha	Obs	Alpha	Obs	Alpha
Panel A.1: Value-Weighted Distress Risk Portfolios								
1 (Low Distress)	605	0.15	99	0.31	39	0.34	33	0.55
2	600	0.13	97	0.17	38	0.14	33	0.36
3	602	–0.02	97	0.18	38	0.13	32	0.36
4	595	–0.13	97	0.10	38	0.02	33	0.01
5 (High Distress)	565	–0.29	95	–0.16	37	–0.36	31	–0.73
High–Low		–0.43		–0.47		–0.70		–1.28
t-statistic		[–2.58]		[–2.74]		[–2.73]		[–3.05]
Panel A.2: Equally-Weighted Distress Risk Portfolios								
1 (Low Distress)	605	0.20	99	0.32	39	0.41	33	0.61
2	600	0.21	97	0.22	38	0.28	33	0.38
3	602	0.05	97	0.24	38	0.24	32	0.38
4	595	–0.13	97	0.16	38	0.14	33	0.02
5 (High Distress)	565	–0.30	95	–0.15	37	–0.29	31	–0.74
High–Low		–0.50		–0.47		–0.70		–1.34
t-statistic		[–2.47]		[–2.81]		[–2.72]		[–3.10]

Table 3 continued

Panel B: First Sorting Variable: Distress Risk; Second: Credit Rating								
	Distress Risk							
	Q1		Q2		Q3		Q4	
Credit Rating	Obs	Alpha	Obs	Alpha	Obs	Alpha	Obs	Alpha
Panel B.1: Value-Weighted Distress Risk Portfolios								
Investment Grade	756	0.15	747	0.08	744	–0.12	708	–0.27
Speculative	122	0.23	123	0.10	125	0.15	138	–0.12
Highly Speculative	44	0.26	44	0.09	45	–0.04	45	–0.22
Junk	42	0.57	42	0.30	42	0.32	36	–0.14
High–Low		0.42		0.22		0.44		0.13
t-statistic		[4.52]		[1.87]		[3.39]		[0.51]
Panel B.2: Equally-Weighted Distress Risk Portfolios								
Investment Grade	756	0.20	747	0.17	744	–0.09	708	–0.29
Speculative	122	0.27	123	0.18	125	0.18	138	–0.06
Highly Speculative	44	0.33	44	0.18	45	0.09	45	–0.20
Junk	42	0.62	42	0.44	42	0.37	36	–0.08
High–Low		0.42		0.26		0.46		0.21
t-statistic		[4.69]		[2.79]		[2.89]		[0.88]

Table 4: Asset Portfolios Univariately Sorted on Firm-Level Distress Risk

In this table, we present the nine-factor model alphas of portfolios of firms' assets univariately sorted on firm-level distress risk. We form the portfolios by sorting assets into portfolios according to the decile breakpoints of our firm-level distress risk proxy at the end of month $t-1$. We calculate a firm's asset return as a value-weighted average of its common stock return and its aggregate bond return. We either use the book values of equity and total liabilities ("book leverage asset return") or the market value of equity and the book value of total liabilities to compute the weights ("market leverage asset return"). The aggregate bond return is a value-weighted average of the returns on all of the firm's outstanding bond issues, using notional amounts to calculate the weights. The firm-level distress risk proxy is Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. We either value- or equally-weight the portfolios and hold them over month t. We also form a spread portfolio long the highest distress risk decile and short the lowest ("High–Low"). The table reports the time-series average of the cross-sectional averages of distress risk, the average numbers of assets per portfolio, and the Bai et al. (2019) nine-factor alphas per portfolio. Average distress risk and the alphas are in monthly percentage terms. See the caption of Table 2 for details on how we calculate the nine-factor model alpha. Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are in parentheses.

			Value-Weighted Portfolios		Equally-Weighted Portfolios	
Decile	Mean Dist. Risk	Mean # Firms	Book Lev. Asset Return 9 Factor Alpha	Market Lev. Asset Return 9 Factor Alpha	Book Lev. Asset Return 9 Factor Alpha	Market Lev. Asset Return 9 Factor Alpha
1 (L)	0.01	54	0.31	0.50	0.26	0.28
2	0.02	53	0.30	0.36	0.26	0.31
3	0.02	54	0.25	0.34	0.22	0.29
4	0.03	53	0.23	0.27	0.22	0.25
5	0.04	53	0.28	0.31	0.29	0.35
6	0.04	54	0.24	0.29	0.22	0.32
7	0.06	54	0.24	0.32	0.22	0.24
8	0.08	54	0.14	0.09	0.18	0.19
9	0.12	54	0.36	0.35	0.21	0.17
10 (H)	0.54	53	0.09	0.12	0.01	-0.01
High–Low			–0.22	–0.38	–0.24	–0.28
t-statistic			[–1.24]	[–1.90]	[–1.98]	[–1.88]

Table 5: Bond and Stock Portfolios Double-Sorted on Firm-Level Distress Risk and Shareholder Advantage

In this table, we present the nine-factor model alphas of bond and stock portfolios double-sorted on firm-level distress risk and shareholder advantage. We form the portfolios by first sorting bonds or stocks into portfolios according to the tercile breakpoints of one of the shareholder advantage proxies at the end of month $t-1$. Within each shareholder advantage portfolio, we then sort them into portfolios according to the quartile breakpoints of our firm-level distress risk proxy at the same time. The firm-level distress risk proxy is Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. The shareholder advantage proxy is R&D intensity (Panel A), the sales-based Herfindahl index (Panel B), and asset tangibility (Panel C), with a low R&D intensity, a high Herfindahl index, and a low asset tangibility indicating strong shareholder advantage. R&D intensity is R&D expenses scaled by total assets. The Herfindahl index is the sum over firms' squared sales proportions within an industry. Asset tangibility is gross PP&E scaled by total assets. In case of R&D intensity, we are only able to sort into two (median-based) shareholder advantage portfolios since most firms have a zero R&D intensity. We either value- or equally-weight the portfolios and hold them over month t. We calculate the bond weights using notional bond values outstanding and the stock weights using market equity values. Within each shareholder advantage portfolio, we form a spread portfolio long the highest distress risk portfolio and short the lowest ("High–Low"). The table shows the Bai et al. (2018) nine-factor alphas for those double-sorted portfolios within the highest or lowest shareholder advantage portfolio. The alphas are in monthly percentage terms. See the caption of Table 2 for details on how we calculate the nine-factor model alpha. Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are in parentheses.

	Value-Weighted Portfolios				Equally-Weighted Portfolios			
	Bonds Shareholder Power		Stocks Shareholder Power		Bonds Shareholder Power		Stocks Shareholder Power	
Portfolio	Strong	Weak	Strong	Weak	Strong	Weak	Strong	Weak
Panel A: Shareholder Power Proxy = R&D Expenses								
1 (L)	0.20	0.13	–0.09	0.02	0.26	0.19	–0.04	0.10
2	0.03	0.15	–0.10	0.04	0.15	0.22	0.07	0.18
3	–0.04	0.05	–0.18	0.21	–0.02	0.12	0.06	0.20
4 (H)	–0.18	–0.39	–0.45	–0.18	–0.24	–0.38	–0.36	0.09
High–Low	–0.38	–0.52	–0.35	–0.20	–0.50	–0.57	–0.33	–0.01
t-statistic	[–2.76]	[–2.53]	[–1.08]	[–0.63]	[–3.06]	[–2.45]	[–1.18]	[–0.03]
Panel B: Shareholder Power Proxy = Herfindahl Index								
1 (L)	0.17	0.18	0.01	–0.31	0.24	0.20	0.03	–0.12
2	0.18	0.09	0.06	–0.10	0.25	0.20	0.06	0.03
3	–0.09	–0.05	0.02	–0.04	0.01	–0.11	0.04	0.15
4 (H)	–0.25	–0.16	–0.62	–0.39	–0.22	–0.22	–0.31	–0.10
High–Low	–0.42	–0.34	–0.62	–0.08	–0.46	–0.43	–0.34	0.02
t-statistic	[–2.34]	[–2.44]	[–2.05]	[–0.26]	[–2.44]	[–2.43]	[–1.34]	[0.08]

Table 5 continued

Panel C: Shareholder Power Proxy = Asset Tangibility								
1 (L)	0.17	0.18	–0.01	0.03	0.23	0.28	0.07	0.08
2	0.10	0.05	0.06	–0.06	0.15	0.18	0.14	0.03
3	0.06	–0.03	0.15	–0.08	0.14	–0.04	0.16	0.05
4 (H)	–0.14	–0.30	–0.48	–0.30	–0.10	–0.27	–0.13	–0.34
High–Low	–0.31	–0.48	–0.47	–0.34	–0.33	–0.55	–0.20	–0.42
t-statistic	[–2.48]	[–2.38]	[–1.10]	[–0.95]	[–2.26]	[–2.76]	[–0.85]	[–1.01]

Table 6: Regressions on Distress Risk and Shareholder Advantage

This table shows the results from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead excess bond returns (Panel A) and excess stock returns (Panel B) on our firm-level distress risk proxy, the shareholder advantage proxies, interactions between the distress risk and the shareholder advantage proxies, and control variables. The firm-level distress risk proxy is the natural log of Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. The shareholder advantage proxies are based on R&D intensity, the sales-based Herfindahl index, and asset tangibility. LowR&D is a dummy variable equal to one if R&D expenses scaled by total assets is below the third quartile per month, else zero. HighHSI is a dummy variable equal to one if the Herfindahl index, the sum over firms' squared sales proportions within an industry, is above its median per month, elso zero. LowTangibility is a dummy variable if gross PP&E scaled by total assets is below its median per month, else zero. In case of the bond return regressions, the control variables are $\beta^{MKT^{Stock}}$, β^{SMB}, β^{HML}, β^{TERM}, β^{DEF}, $\beta^{MOM^{Stock}}$, β^{LIQ}, $\beta^{MKT^{Bond}}$ and $\beta^{MOM^{Bond}}$, years-to-maturity, the natural log of bond amount outstanding, the most recent credit rating, and the lagged excess bond return. In case of the stock return regressions, the control variables are $\beta^{MKT^{Stock}}$, β^{TERM}, β^{DEF}, β^{LIQ}, $\beta^{MKT^{Bond}}$, $\beta^{MOM^{Bond}}$, the natural log of market equity, the natural log of book-to-market ratio, and the past eleven-month return. Betas are estimated using two-year rolling windows and are winsorized at the first and 99th percentiles. To keep the table concise, we do not report the estimates on the control variables. Plain numbers are estimates, in monthly percentage terms. Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are in parentheses. The final row of each panel further shows the average adjusted R^2 obtained from each Fama and MacBeth (1973) regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Bond Return Regressions				
Distress	–0.26	–0.23	–0.23	–0.27	–0.20	–0.23	–0.28	–0.24
	[–3.23]	[–2.91]	[–2.05]	[–3.15]	[–2.41]	[–2.92]	[–2.89]	[–1.54]
LowR&D		0.10	0.07					–0.02
		[1.94]	[0.09]					[–0.03]
Distress × *LowR&D*			0.01					0.00
			[0.07]					[–0.01]
HighHSI				–0.06	–0.80			–0.22
				[–1.77]	[–1.21]			[–0.38]
Distress × *HighHSI*					–0.10			–0.02
					[–1.19]			[–0.29]
LowTangibility						–0.03	0.80	0.45
						[–0.81]	[1.15]	[0.74]
Distress × *LowTangibility*							0.11	0.06
							[1.25]	[0.89]
Constant	–1.40	–1.26	–1.26	–1.43	–0.87	–1.14	–1.46	–1.13
	[–1.60]	[–1.32]	[–1.06]	[–1.61]	[–0.88]	[–1.21]	[–1.41]	[–0.78]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.36	0.37	0.38	0.37	0.37	0.38	0.38	0.40

Table 6 continued

Panel B: Stock Return Regressions								
Distress	–0.06	–0.05	0.19	–0.06	0.08	–0.06	–0.05	0.37
	[–0.48]	[–0.39]	[1.48]	[–0.47]	[0.54]	[–0.46]	[–0.39]	[2.51]
LowR&D		–0.22	–2.65					–2.69
		[–1.45]	[–2.38]					[–2.36]
Distress × *LowR&D*			–0.30					–0.31
			[–2.36]					[–2.30]
HighHSI				–0.18	–2.18			–2.22
				[–1.20]	[–2.10]			[–2.24]
Distress × *HighHSI*					–0.25			–0.26
					[–2.11]			[–2.25]
LowTangibility						0.05	–0.01	–0.36
						[0.40]	[–0.01]	[–0.38]
Distress × *LowTangibility*							0.00	–0.04
							[–0.02]	[–0.38]
Constant	2.18	2.43	4.35	2.26	3.36	2.14	2.23	5.92
	[1.15]	[1.23]	[2.29]	[1.20]	[1.62]	[1.16]	[1.23]	[3.09]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.13

Table 7: Stock and Bond Portfolios Double-Sorted on Firm-Level Distress Risk and Disinvestment Option Value

In this table, we present the nine-factor model alphas of bond and stock portfolios double-sorted on firm-level distress risk and disinvestment option value. We form the portfolios by first sorting bonds or stocks into portfolios according to the tercile breakpoints of one of the disinvestment option value proxies at the end of month $t-1$. Within each disinvestment option value portfolio, we then sort them into portfolios according to the quartile breakpoints of our firm-level distress risk proxy at the same time. The firm-level distress risk proxy is Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. The disinvestment option value proxies are operating profitability (Panel A) and capacity overhang (Panel B), with a lower operating profitability and a higher capacity overhang signalling more valuable disinvestment options. Operating profitability is gross profits scaled by total assets, while capacity overhang is an estimate of the difference between a firm's installed productive capacity and its optimal capacity derived using a stochastic frontier model. We either value- or equally-weight the portfolios and hold them over month t. We calculate the bond weights using notional bond values outstanding and the stock weights using market equity values. Within each disinvestment option value portfolio, we form a spread portfolio long the highest distress risk portfolio and short the lowest ("High–Low"). The table shows the Bai et al. (2018) nine-factor alphas for those double-sorted portfolios within the highest or lowest shareholder advantage portfolio. The alphas are in monthly percentage terms. See the caption of Table 2 for details on how we calculate the nine-factor model alpha. Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are in parentheses.

	Value-Weighted Portfolios				Equally-Weighted Portfolios			
	Bonds Divest. Option		Stocks Divest. Option		Bonds Divest. Option		Stocks Divest. Option	
Portfolio	Low	High	Low	High	Low	High	Low	High
Panel A: Divestment Option Proxy = Firm Profitability								
1 (L)	0.17	0.22	0.07	–0.40	0.23	0.30	0.15	–0.10
2	0.13	–0.03	0.08	0.02	0.20	0.04	0.21	0.19
3	0.08	–0.12	0.15	–0.23	0.16	–0.09	0.24	–0.04
4 (H)	–0.06	–0.35	–0.06	–0.63	–0.03	–0.38	0.32	–0.20
High–Low	–0.24	–0.57	–0.13	–0.23	–0.26	–0.67	0.17	–0.10
t-statistic	[–2.65]	[–2.55]	[–0.49]	[–0.72]	[–2.54]	[–2.53]	[0.78]	[–0.33]
Panel B: Divestment Option Proxy = Capacity Overhang								
1 (L)	0.18	0.18	0.08	–0.04	0.22	0.27	0.16	0.14
2	0.10	0.18	0.03	0.12	0.18	0.24	0.27	0.21
3	0.02	–0.02	0.12	0.25	0.12	0.06	0.28	0.28
4 (H)	–0.06	–0.24	–0.30	–0.38	0.00	–0.28	0.08	–0.15
High–Low	–0.25	–0.42	–0.38	–0.34	–0.22	–0.54	–0.07	–0.28
t-statistic	[–3.04]	[–2.38]	[–1.10]	[–1.05]	[–2.96]	[–2.78]	[–0.31]	[–0.81]

Table 8: Regressions On Distress Risk and Disinvestment Option Value

This table shows the results from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead excess bond returns (Panel A) and excess stock returns (Panel B) on our firm-level distress risk proxy, disinvestment option value proxies, interactions between the distress risk and the disinvestment option value proxies, and control variables. The firm-level distress risk proxy is the natural log of Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. The disinvestment option value proxies are based on operating profitability and capacity overhang, with a lower operating profitability and a higher capacity overhang signalling more valuable disinvestment options. LowGrossProfits is a dummy variable equal to one if gross profits scaled by total assets is below its median per month, else zero. HighOverhang is a dummy variable equal to one if capacity overhang, an estimate of the difference between a firm's installed productive capacity and its optimal capacity derived using a stochastic frontier model, is above its median per month, else zero. In case of the bond return regressions, the control variables are $\beta^{MKT^{Stock}}$, β^{SMB}, β^{HML}, β^{TERM}, β^{DEF}, $\beta^{MOM^{Stock}}$, β^{LIQ}, $\beta^{MKT^{Bond}}$ and $\beta^{MOM^{Bond}}$, years-to-maturity, the natural log of bond amount outstanding, the most recent credit rating, and the lagged excess bond return. In case of the stock return regressions, the control variables are $\beta^{MKT^{Stock}}$, β^{TERM}, β^{DEF}, β^{LIQ}, $\beta^{MKT^{Bond}}$, $\beta^{MOM^{Bond}}$, the natural log of market equity, the natural log of book-to-market ratio, and the past eleven-month return. Betas are estimated using two-year rolling windows and are winsorized at the first and 99th percentiles. To keep the table concise, we do not report the estimates on the control variables. Plain numbers are estimates, in monthly percentage terms. Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are in parentheses. The final row of each panel further shows the average adjusted R^2 obtained from each Fama and MacBeth (1973) regression.

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Bond Return Regressions			
Distress	–0.28	–0.28	–0.21	–0.28	–0.17	–0.10
	[–3.47]	[–3.36]	[–3.16]	[–3.52]	[–3.66]	[–2.22]
LowGrossProfits		0.05	–1.94			–1.82
		[0.77]	[–1.92]			[–1.82]
Distress × *LowGrossProfits*			–0.27			–0.25
			[–2.08]			[–1.96]
HighOverhang				–0.01	–1.92	–1.17
				[–0.18]	[–1.95]	[–2.01]
Distress × *HighOverhang*					–0.17	–0.15
					[–1.98]	[–2.04]
Constant	–1.57	–1.53	–1.09	–1.57	–0.79	–0.08
	[–1.85]	[–1.82]	[–1.44]	[–1.88]	[–1.19]	[–0.12]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R2	0.43	0.43	0.45	0.43	0.44	0.45

Table 8 continued

Panel B: Stock Return Regressions						
Distress	–0.04	–0.03	0.10	–0.03	0.01	0.08
	[–0.28]	[–0.17]	[0.80]	[–0.22]	[0.05]	[0.80]
LowGrossProfits		–0.22	–2.35			–2.33
		[–1.68]	[–2.11]			[–2.22]
Distress × *LowGrossProfits*			–0.27			–0.27
			[–1.90]			[–2.01]
HighOverhang				–0.07	–0.56	0.09
				[–0.81]	[–0.54]	[0.10]
Distress × *HighOverhang*					–0.06	0.02
					[–0.46]	[0.19]
Constant	2.47	2.63	3.52	2.57	2.89	3.43
	[1.21]	[1.29]	[1.99]	[1.27]	[1.62]	[2.06]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R2	0.12	0.12	0.13	0.12	0.12	0.13

Table 9: Stock Portfolios Univariate Sorted on Firm-Level Distress Risk (1981–2017)

In this table, we present the mean excess returns and alphas of stock portfolios univariately sorted on firm-level distress risk over the extended sample period from 1981 to 2017. We form the portfolios by sorting stocks into portfolios according to the decile breakpoints of our firm-level distress risk proxy at the end of month $t-1$. The firm-level distress risk proxy is Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. We either value- (Panel A) or equally-weight the portfolios (Panel B) and hold them over month t. In case of the equally-weighted portfolios, we exclude stocks with a market size below the first quartile at the end of month $t-1$. We calculate the stock weights using market equity values. We also form a spread portfolio long the highest distress risk decile and short the lowest ("High–Low"). The table reports the time-series average of the cross-sectional averages of distress risk, the average numbers of stocks per portfolio, and the average excess stock returns, Fama-French three-factor alphas, and five-factor model alphas for each portfolio. Average distress risk, the average excess returns, and the alphas are in monthly percentage terms. We obtain the alphas from regressing a portfolio's return on the relevant factors and reporting the intercept from that regression. The three factors are the excess stock market return (MKT^{Stock}), the size factor (SMB), and the value factor (HML). The five factors add to the former the stock momentum factor (MOM^{Stock}) and the stock liquidity risk factor (LIQ). Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are given in parentheses.

Decile	Mean Distress Risk	Mean Number Stocks	Mean Excess Return	FF3 Alpha	5-Factor Alpha
		Panel A: Value-Weighted Distress Risk Portfolios			
1 (Low Distress)	0.006	406	0.55	0.03	0.01
2	0.012	406	0.66	0.12	0.02
3	0.018	406	0.49	–0.01	–0.06
4	0.024	406	0.66	0.09	0.05
5	0.033	406	0.74	0.13	0.10
6	0.045	406	0.79	0.15	0.16
7	0.065	406	0.82	0.05	0.09
8	0.104	406	0.83	–0.01	0.12
9	0.199	406	0.34	–0.61	–0.42
10 (High Distress)	0.999	407	0.10	–1.05	–0.62
High–Low			–0.45	–1.07	–0.64
t-statistic			[–1.33]	[–3.72]	[–2.62]
		Panel B: Equally-Weighted Distress Risk Portfolios			
1 (Low Distress)	0.006	304	0.60	–0.05	–0.02
2	0.011	305	0.64	–0.03	–0.04
3	0.016	304	0.71	0.04	0.05
4	0.022	305	0.83	0.12	0.14
5	0.028	305	0.81	0.06	0.11
6	0.037	304	0.80	0.02	0.09
7	0.052	304	0.81	0.00	0.11
8	0.076	305	0.80	–0.07	0.07
9	0.132	304	0.67	–0.30	–0.09
10 (High Distress)	0.545	305	0.37	–0.76	–0.34
High–Low			–0.24	–0.71	–0.32
t-statistic			[–0.91]	[–3.03]	[–1.56]

Table 10: Regressions On Distress Risk and Disinvestment Option Value (1981–2017)

This table shows the results from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead excess stock returns on our firm-level distress risk proxy, disinvestment option value proxies, interactions between the distress risk and the disinvestment option value proxies, and control variables, estimated over over the extended sample period from 1981 to 2017. The regressions exclude stocks with a market size below the first quartile at the end of month $t-1$. The firm-level distress risk proxy is the natural log of Campbell et al.'s (2008) hazard-model probability that a firm fails over the coming twelve months. The disinvestment option value proxies are based on operating profitability and capacity overhang, with a lower operating profitability and a higher capacity overhang signalling more valuable disinvestment options. LowGrossProfits is a dummy variable equal to one if gross profits scaled by total assets is below its median per month, else zero. HighOverhang is a dummy variable equal to one if capacity overhang, an estimate of the difference between a firm's installed productive capacity and its optimal capacity derived using a stochastic frontier model, is above its median per month, else zero. The control variables are $\beta^{MKT^{Stock}}$, β^{LIQ}, the natural logarithm of the market equity value, the natural logarithm of book-to-market ratio and the past 11-month average monthly returns as control variables. Betas are estimated using two-year rolling windows and are winsorized at the first and 99th percentiles. To keep the table concise, we do not report the estimates on the control variables. Plain numbers are estimates, in monthly percentage terms. Newey and West (1987)-adjusted t-statistics calculated using a twelve-month lag-length are in parentheses. The final row of each panel further shows the average adjusted R^2 obtained from each Fama and MacBeth (1973) regression.

	(1)	(2)	(3)	(4)	(5)	(7)
Distress	0.09	0.12	0.18	0.13	0.16	0.22
	[1.43]	[1.78]	[2.75]	[1.89]	[2.45]	[3.29]
LowGrossProfits		–0.36	–1.28			–1.20
		[–4.04]	[–3.36]			[–3.12]
Distress × *LowGrossProfits*			–0.11			–0.11
			[–2.43]			[–2.36]
HighOverhang				–0.33	–0.84	–0.52
				[–3.40]	[–2.46]	[–1.50]
Distress × *HighOverhang*					–0.06	–0.03
					[–1.62]	[–0.80]
Constant	1.30	1.58	2.08	1.60	1.93	2.44
	[1.42]	[1.72]	[2.33]	[1.72]	[2.07]	[2.67]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R2	0.05	0.06	0.06	0.06	0.06	0.06

A Appendix: The Fan and Sundaresan (2000) Model

A.1 Valuing the Equity and Debt Claims

Using contingent claims analysis, Fan and Sundaresan (2000) show that the value of a firm's levered assets in their shareholder advantage model, $\upsilon(V)$, is equal to:

$$\upsilon(V) = \begin{cases} V + \frac{\tau c}{r} - \frac{\lambda_2}{\lambda_2 - \lambda_1}\frac{\tau c}{r}\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} & \text{if } V > \tilde{V}_S, \\ V + \frac{-\lambda_1}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_2} & \text{if } V \leq \tilde{V}_S, \end{cases} \tag{A1}$$

where the optimal (endogenous) strategic default threshold $\tilde{V}_S$ is given by:

$$\tilde{V}_S = \frac{c(1-\tau+\eta\tau)}{r}\frac{-\lambda_1}{1-\lambda_1}\frac{1}{1-\eta\alpha}, \tag{A2}$$

and:

$$\lambda_1 = \left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right) - \sqrt{\left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right)^2 + \frac{2r}{\sigma^2}} < 0, \tag{A3}$$

$$\lambda_2 = \left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right)^2 + \frac{2r}{\sigma^2}} > 1. \tag{A4}$$

Conversely, they show that the value of equity, $\tilde{E}(V)$, is equal to:

$$\tilde{E}(V) = \begin{cases} V - \frac{c(1-\tau)}{r} + \left[\frac{c(1-\tau)}{(1-\lambda_1)r} - \frac{\lambda_1(1-\lambda_2)\eta}{(\lambda_2-\lambda_1)(1-\lambda_1)}\frac{\tau c}{r}\right]\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} & \text{if } V > \tilde{V}_S, \\ \theta^* \upsilon(V) & \text{if } V \leq \tilde{V}_S, \end{cases} \tag{A5}$$

where θ^* is given in Equation (4) in the main text. Finally, the value of debt, $\tilde{D}(V)$, is the value of the levered assets minus the value of equity, $\upsilon(V) - \tilde{E}(V)$.

A.2 Deriving the Expected Equity Value

Garlappi et al. (2008) show that the time-0 expectation of the equity value at time t, $\mathbb{E}_0(\tilde{E}(V_t))$, is:

$$\mathbb{E}_0(\tilde{E}(V_t)) = \eta\alpha V_0 e^{(\mu-\delta)t} N\left(h(t) - \sigma\sqrt{t}\right)$$

$$
\begin{aligned}
&- \quad \eta \frac{\lambda_1}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_2} e^{\lambda_2(\gamma-\lambda_2)t} N\left(h(t)-\lambda_2\sigma\sqrt{t}\right) \\
&+ \quad V_0 e^{(\mu-\delta)t} N\left(-h(t)+\sigma\sqrt{t}\right) - \frac{c(1-\tau)}{r} N\left(-h(t)\right) \\
&+ \quad \left[\frac{c(1-\tau)}{(1-\lambda_1)r} - \frac{\lambda_1(1-\lambda_2)\eta}{(\lambda_2-\lambda_1)(1-\lambda_1)}\frac{\tau c}{r}\right]\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} \\
&\times \quad e^{\lambda_1(\gamma-\lambda_1)t} N\left(-h(t)+\lambda_1\sigma\sqrt{t}\right), \qquad \text{(A6)}
\end{aligned}
$$

where $\gamma = \mu - \delta - \frac{1}{2}\sigma^2$, $h(t) = \frac{\ln(\tilde{V}_S/V_0)-\gamma t}{\sigma\sqrt{t}}$, and $N(.)$ is the cumulative standard normal distribution.

They further show that the probability of the unlevered asset value V hitting the strategic default threshold $\tilde{V}_S$ over the period from $t=0$ to T ("strategic default risk"), $\Pr_{(0,T]}$ is:

$$
\Pr_{(0,T]} = N\left(\frac{\ln(\tilde{V}_S)-\ln(V_0)-\gamma T}{\sigma\sqrt{T}}\right) + e^{\frac{2\gamma(\ln(\tilde{V}_S)-\ln(V_0))}{\sigma^2}} N\left(\frac{\ln(\tilde{V}_S)-\ln(V_0)+\gamma T}{\sigma\sqrt{T}}\right). \qquad \text{(A7)}
$$

A.3 Deriving the Expected Debt Value

In this section, we apply the methods used in Garlappi et al. (2008) to derive the time 0 expectation of the debt value at time t, $\mathbb{E}_0(\tilde{E}(V_t))$. Given that $\tilde{D}(V) = \upsilon(V) - \tilde{E}(V)$, we can easily achieve that goal by deriving the time 0 expectation of the levered asset value at time t, $\mathbb{E}_0(\upsilon(V_t))$. Under the assumptions in Section 4.1, the unlevered asset value at time t can be written as:

$$
V_t = V_0 e^{(\mu-\delta-\frac{1}{2}\sigma^2)t+\sigma(B_t-B_0)}, \qquad \text{(A8)}
$$

which is log-normally distributed. Again defining $\gamma = \mu-\delta-\frac{1}{2}\sigma^2$, the location and scale parameters of the natural log of V_t are $E[\ln V_t] = \ln V_0 + \gamma t$ and $\mathrm{Var}[\ln V_t] = \sigma^2 t$, respectively.

Consider the integral $\int_0^a V_t^b p(V_t) dV_t$, where a and b are constants and $p(V_t)$ is the probability density function of the log-normal variable V_t. Plugging in for $p(V_t)$, we obtain:

$$
\int_0^a V_t^b p(V_t) dV_t = \int_0^a V_t^b \frac{1}{\sqrt{2\pi\sigma^2 t}V_t} e^{-\frac{1}{2}\left(\frac{\ln V_t - (\ln V_0 + \gamma t)}{\sigma\sqrt{t}}\right)^2} dV_t. \qquad \text{(A9)}
$$

Using the change of variable $X_t = \frac{\ln V_t - \ln V_0 - \gamma t}{\sigma\sqrt{t}}$, we can rewrite the right-hand side as:

$$
\begin{aligned}
& \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} e^{b(\ln V_0 + \gamma t + \sigma\sqrt{t}X_t)} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}X_t^2} dX_t && \text{(A10)} \\
= \; & V_0^b e^{b\gamma t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}X_t^2 + b\sigma\sqrt{t}X_t - \frac{1}{2}b^2\sigma^2 t + \frac{1}{2}b^2\sigma^2 t} dX_t && \text{(A11)} \\
= \; & V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(X_t^2 - 2b\sigma\sqrt{t}X_t + b^2\sigma^2 t)} dX_t && \text{(A12)} \\
= \; & V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(X_t - b\sigma\sqrt{t})^2} dX_t. && \text{(A13)}
\end{aligned}
$$

Using the change of variable $Y_t = X_t - b\sigma\sqrt{t}$, we can write:

$$
\begin{aligned}
& V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}} - b\sigma\sqrt{t}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}Y_t^2} dY_t && \text{(A14)} \\
= \; & V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} N\left(\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}} - b\sigma\sqrt{t}\right). && \text{(A15)}
\end{aligned}
$$

Following the same steps, we can, conversely, also show that:

$$
\int_a^{\infty} V_t^b p(V_t) dV_t = V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} N\left(-\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}} + b\sigma\sqrt{t}\right). \qquad \text{(A16)}
$$

Using Equation (A5), we can write the expected levered asset value, $\mathbb{E}_0(\upsilon(V_t))$, as:

$$
\begin{aligned}
\mathbb{E}_0(\upsilon(V_t)) \; = \; & \int_0^{\infty} V_t p(V_t) dV_t + \int_{\tilde{V}_S}^{\infty} \frac{\tau c}{r} p(V_t) dV_t - \int_{\tilde{V}_S}^{\infty} \frac{\lambda_2}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V_t}{\tilde{V}_S}\right)^{\lambda_1} p(V_t) dV_t \\
+ \; & \int_0^{\tilde{V}_S} \frac{-\lambda_1}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V_t}{\tilde{V}_S}\right)^{\lambda_2} p(V_t) dV_t \\
= \; & \int_0^{\infty} V_t p(V_t) dV_t + \frac{\tau c}{r} \int_{\tilde{V}_S}^{\infty} p(V_t) dV_t - \frac{\lambda_2}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{1}{\tilde{V}_S}\right)^{\lambda_1} \int_{\tilde{V}_S}^{\infty} V_t^{\lambda_1} p(V_t) dV_t \\
+ \; & \frac{-\lambda_1}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{1}{\tilde{V}_S}\right)^{\lambda_2} \int_0^{\tilde{V}_S} V_t^{\lambda_2} p(V_t) dV_t. \qquad \text{(A17)}
\end{aligned}
$$

Using Equations (A15) and (A16), we finally have:

$$
\mathbb{E}_0(\upsilon(V_t)) \; = \; V_0 e^{(\mu-\delta)t} + \frac{\tau c}{r} N(-h(t))
$$

$$
\begin{aligned}
- &\quad \frac{\lambda_2}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_1} e^{\lambda_1(\gamma+\frac{1}{2}\lambda_1\sigma^2)t} N\left(-h(t)+\lambda_1\sigma\sqrt{t}\right) \\
+ &\quad \frac{-\lambda_1}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_2} e^{\lambda_2(\gamma+\frac{1}{2}\lambda_2\sigma^2)t} N\left(h(t)-\lambda_2\sigma\sqrt{t}\right), \qquad \text{(A18)}
\end{aligned}
$$

where we again use $h(t) = \frac{\ln(\tilde{V}_S/V_0)-\gamma t}{\sigma\sqrt{t}}$ to simplify the notation.

B Appendix: A Real Options Model with Disinvestment

B.1 Valuing the Operating Assets of the Firm

We use contingent claims analysis to value the *incremental* production options owned by the firm described in Section 5.1.1. Using $K \in \{0; \bar{K})$ to number the incremental options, incremental option K produces a cash flow of $\theta - c_1 - c_2K - f$ per time unit when switched on to produce output and a payoff of $-f$ per time unit when switched off. Denoting the value of incremental option K by $\Delta V(\theta; K)$ and assuming that there is a traded asset whose value perfectly replicates variations in the price θ, it is well known that the value of incremental option K has to satisfy:

$$
\frac{1}{2}\sigma^2\theta^2\frac{\partial^2\Delta V(\theta;K)}{\partial\theta^2} + (r-\delta)\theta\frac{\partial\Delta V(\theta;K)}{\partial\theta} - r\Delta V(\theta;K) + \pi(\theta,K) = 0, \qquad \text{(B1)}
$$

where $\pi(\theta, K)$ is the cash flow produced by the option.

In the θ-region in which the firm uses the incremental option to produce output (i.e., in which $\pi(\theta, K) = \theta - c_1 - c_2K - f$), the value of the option takes on the general form:

$$
\Delta V(\theta, K) = A_O\theta^{\beta_1} + B_O\theta^{\beta_2} + \frac{\theta}{\delta} - \frac{c_1 + c_2K + f}{r}, \qquad \text{(B2)}
$$

where A_O and B_O are free parameters, and:

$$
\beta_1 = \frac{1}{2} - (r-\delta)/\sigma^2 + \sqrt{\left[(r-\delta)/\sigma^2 - \frac{1}{2}\right]^2 + 2r/\sigma^2} > 1, \qquad \text{(B3)}
$$

$$\beta_2 = \frac{1}{2} - (r-\delta)/\sigma^2 - \sqrt{\left[(r-\delta)/\sigma^2 - \frac{1}{2}\right]^2 + 2r/\sigma^2} < 0. \tag{B4}$$

Given that $\lim_{\theta\to+\infty} \Delta V(\theta, K)$ needs to be $\frac{\theta}{\delta} - \frac{c_1+c_2K+f}{r}$, it is obvious that $A_O = 0$. Conversely, in the region in which the firm does not use the incremental option to produce output (i.e., in which $\pi(\theta, K) = -f$), the value of the option takes on the general form:

$$\Delta V(\theta, K) = A_I\theta^{\beta_1} + B_I\theta^{\beta_2} + -\frac{f}{r}, \tag{B5}$$

where A_I and B_I are free parameters. Finally, in the region in which the firm instantaneously sells the option (i.e., when θ drops below the disinvestment threshold θ^D, which is another free parameter), the value of the incremental option is equal to the disinvestment price s.

To find the values of the free parameters B_O, A_I, B_I, and θ^D, we ensure that the three regions value-match and smooth-paste into one another. In particular, we ensure that:

$$B_O(\theta^P)^{\beta_2} + \frac{(\theta^P)}{\delta} - \frac{c_1+c_2K+f}{r} = A_I(\theta^P)^{\beta_1} + B_I(\theta^P)^{\beta_2} - \frac{f}{r}, \tag{B6}$$

$$B_O\beta_2(\theta^P)^{\beta_2-1} + \frac{1}{\delta} = A_I\beta_1(\theta^P)^{\beta_1-1} + B_I\beta_2(\theta^P)^{\beta_2-1}, \tag{B7}$$

$$A_I(\theta^D)^{\beta_1} + B_I(\theta^D)^{\beta_2} - \frac{f}{r} = s, \tag{B8}$$

$$A_I\beta_1(\theta^D)^{\beta_1-1} + B_I\beta_2(\theta^D)^{\beta_2-1} = 0, \tag{B9}$$

where $\theta^D = c_1+c_2K$ is the price θ at which the firm switches on the incremental option. Equation (B6) ensures that at θ^P the value of the used option is identical to the value of the idle option, while Equation (B7) ensures that, at that price, the two option values do so with identical partial derivatives (i.e., smoothly). Conversely, Equation (B8) ensures that at the price at which the firm disinvests off the incremental option, θ^D, the value of the option is identical to the disinvestment price, while Equation (B9) ensures that, at that price, the option value has a zero partial derivative.

Solving for B_O, A_I, B_I, and θ^D, we obtain:

$$p^D = \left(\frac{r\delta(\beta_1 - \beta_2)(s + \frac{f}{r})(c_1 + c_2 K)^{\beta_1 - 1}}{(r - \beta_2(r - \delta))\left(1 - \frac{\beta_1}{\beta_2}\right)} \right)^{\frac{1}{\beta_1}}, \tag{B10}$$

$$A_I = \frac{s + \frac{f}{r}}{(p^D)^{\beta_1}\left(1 - \frac{\beta_1}{\beta_2}\right)}, \tag{B11}$$

$$B_I = \frac{s + \frac{f}{r}}{(p^D)^{\beta_2}\left(1 - \frac{\beta_2}{\beta_1}\right)}, \tag{B12}$$

$$B_O = A_I(c_1 + c_2 K)^{\beta_1 - \beta_2} - \left(\frac{r - \delta}{r\delta}\right)(c_1 + c_2 K)^{1 - \beta_2} + B_I. \tag{B13}$$

Having valued the incremental options, total firm value, $V(\theta, \bar{K})$, is now:

$$V(\theta, \bar{K}) = \int_0^{\bar{K}} \Delta V(\theta, K) dK, \tag{B14}$$

and the expected instantaneous excess asset return of the firm, $E[R_A] - r$, is:

$$E[R_A] - r = \frac{\partial V(\theta, \bar{K})}{\partial \theta} \times \frac{\theta}{V(\theta, \bar{K})} \times (\mu - r), \tag{B15}$$

as shown in, for example, Cox and Rubinstein (1985) or Carlson et al. (2004).

C Appendix: Measuring Capacity Overhang

Aretz and Pope (2018) use a stochastic frontier model to estimate the difference between a firm's installed production capacity and the capacity level setting the marginal benefit of additional capacity equal to its marginal cost ("optimal capacity"). As they show, real options models often imply that installed capacity cannot fall below optimal capacity, implying that the difference between the two capacity levels is truncated from below at zero. Given that, stochastic frontier models are an appealing method to estimate the difference. Intuitively speaking, such models decompose a variable (in this case:

installed capacity) into a component capturing the minimum value the variable can take on (optimal capacity) and a positively-signed residual component ("capacity overhang"). More specifically, we can write a stochastic frontier model decomposing a firm's installed capacity as:

$$\ln(\bar{K}_{i,t}) = \alpha_k + \boldsymbol{\beta}'\mathbf{X}_{i,t} + v_{i,t} + u_{i,t} = \alpha_k + \boldsymbol{\beta}'\mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{C1}$$

where $\bar{K}_{i,t}$ is installed capacity, $\alpha_k + \boldsymbol{\beta}'\mathbf{X}_{i,t} + v_{i,t}$ optimal capacity, $u_{i,t}$ capacity overhang, and $\epsilon_{i,t} \equiv v_{i,t} + u_{i,t}$. Optimal capacity is modeled as a linear function of industry fixed effects, α_k, optimal capacity determinants contained in the vector $\mathbf{X}_{i,t}$, and a normally distributed residual $v_{i,t}$, with mean zero and variance σ_v^2. Conversely, capacity overhang, $u_{i,t}$, is a normally-distributed residual truncated from below at zero. The mean of the normally-distributed variable, $\boldsymbol{\gamma}'\boldsymbol{Z}_{i,t}$, is modeled as a linear function of capacity overhang determinants contained in the vector $\boldsymbol{Z}_{i,t}$, while its variance is σ_u^2. Finally, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are parameter vectors. The parameter vectors and variance parameters are estimated recursively using maximum likelihood techniques. The first estimation window is July 1963 to December 1971, and the end of the estimation window is rolled forward on an annual basis until December 2017.

Having estimated the parameters, the estimates obtained from the window ending with year $t-1$ are combined with the values of the optimal capacity determinants and capacity overhang determinants for year t. We then define $\mu_{i,t}^* = \frac{\epsilon_{i,t}\sigma_u^2 + \boldsymbol{\gamma}'\boldsymbol{Z}_{i,t}\sigma_v^2}{\sigma_u^2+\sigma_v^2}$ and $\sigma_{i,t}^* = \sigma_u\sigma_v/\sqrt{\sigma_u^2+\sigma_v^2}$. We finally calculate firm i's capacity overhang at time t as the conditional expectation of the capacity overhang residual:

$$\hat{u}_{i,t} = E[u_{i,t}|\epsilon_{i,t}, \boldsymbol{Z}_{i,t}] = \mu_{i,t}^* + \sigma_{i,t}^* \left(\frac{n(-\mu_{i,t}^*/\sigma_{i,t}^*)}{N(\mu_{i,t}^*/\sigma_{i,t}^*)} \right), \tag{C2}$$

where $n(.)$ and $N(.)$ are the standard normal-density and -cumulative density, respectively.

Aretz and Pope (2018) use the log of the sum of gross property, plant, and equipment and intangible assets (intan or intanq) to measure installed capacity.[14] As optimal capacity determinants, they use:

- Sales: Log of sales over the prior four fiscal quarters (sale or saleq).
- COGS: Log of COGS over the prior four fiscal quarters (cogs or cogsq).
- SG&A: Log of SGA costs over the prior four quarters (xsga or xsgaq).

[14] The terms in parentheses are the database (CRSP or Compustat) mnemonics.

- Volatility: Log of the volatility of daily returns (ret) over the prior twelve months.
- Market beta: Sum of slope coefficients from a stock-level regression of excess stock returns (ret) on current, one-day lagged, and the sum of two-, three-, and four-day lagged excess market returns, where the regression is run using daily data over the prior twelve months (see Lewellen and Nagel (2006) for more details about the market beta estimation methodology).
- Risk-free rate: Three-month Treasury bill rate (see Kenneth French's website).

As capacity overhang determinants, they use:

- Recent sales decline: Percentage decrease in sales (sale or saleq) over the most recent four fiscal quarters; the variable is set to zero if the decrease is negative.
- More distant sales decline: Percentage decrease in sales (sale or saleq) from a stock's historical maximum of sales, measured twelve months ago, to its sales twelve months ago; the variable is set to zero if the decrease is negative.
- Loss dummy: Dummy set equal to one if a firm ran a loss (negative ni or niq) over the prior four fiscal quarters; otherwise, the variable is set to zero.

To improve timeliness, Aretz and Pope (2018) use the most recent quarterly estimate of installed capacity whenever quarterly accounting data are available. Else they use the most recent estimate from annual accounting data. With the same objective, they use four-quarter trailing sums of accounting flow variables (e.g., sales, COGS, and SG&E) whenever quarterly accounting data are available. Else they use annual accounting data. In line with Campbell et al. (2008), they assume that quarterly accounting data are released with a two-month reporting gap, while annual accounting data are released with a three-month reporting gap. They use stock market data from CRSP, accounting data from Compustat, and data on the market return and risk-free rate from Kenneth French's website.