

# Real Disinvestments and the Distress Anomaly: Evidence from Stocks, Bonds, and Loans

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January 2026

## Abstract

We argue that firms' ability to disinvest real assets helps rationalize the negative distress premiums in stocks, bonds, and, as we show, loans and firm assets. Using a real-options model in which shareholders and debtholders share disinvestment proceeds, the model suggests that the stock (debt) distress premium becomes more negative with the proceeds paid out to that class, and that both premiums can be negative when debtholders receive most of the proceeds. Using hard-asset disinvestment-ability proxies, the stock (bond or loan) distress premium becomes less (more) negative with those proxies, possibly suggesting that shareholders benefit more strongly from non-secured-asset disinvestments.

JEL CLASSIFICATION: G11; G12.

KEYWORDS: Distress risk; stocks, bonds, loans, and firm assets; real disinvestment options.

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# I. Introduction

Many empirical studies find a flat, hump-shaped, or negative relation between (physical) corporate distress risk proxies and stock returns (“distress anomaly;” see, e.g., [Dichev \(1998\)](#) and [Campbell, Hilscher, and Szilagyi \(2008\)](#)).<sup>1</sup> In addition, [Avramov, Chordia, Jostova, and Philipov \(2022\)](#) find a negative relation between their ratings-based distress risk proxy and corporate bond returns. As they argue, the jointly non-positive distress premiums cast a serious blow to existing theories aiming to rationalize the distress anomaly. More specifically, while [Garlappi, Shu, and Yan \(2008\)](#) and [Garlappi and Yan \(2011\)](#) claim that the distress anomaly arises from shareholders’ ability to extract rents from debtholders in distress (“shareholder advantage theory;” see also [Favara, Schroth, and Valta \(2012\)](#), [Hackbarth, Haselmann, and Schoenherr \(2015\)](#), and [Aretz, Florackis, and Kostakis \(2018\)](#)), their theory predicts a positive — not negative — debt distress premium. Similarly, while [Conrad, Kapadia, and Xing \(2014\)](#) claim that the anomaly arises from investors’ preference for positively skewed returns, their theory also fails to predict a negative debt distress premium. The depressing yet unavoidable conclusion is that we are back to square one in finding a rationale for the distress anomaly.

Our study offers a new rationale for the distress anomaly grounded in firms’ ability to disinvest real assets in distress (“disinvestment rationale”). We first establish that the anomaly does not only emerge in stocks and bonds but also in traded loans and firm assets, measured, as in [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#), as the value-weighted combination of stocks, bonds, and loans reflecting (real) assets. The negative premium in firm assets suggests

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<sup>1</sup>Noteworthy, [Linnainmaa and Roberts \(2018\)](#) report that, in contrast to most other stock anomalies, the distress anomaly also arises over sample periods before and after that over which it was discovered.

that the anomaly could be driven by operational (and not financial) risk. To study that possibility, we allow for stock and debt claims in a standard real options model with capacity utilization, investment, and disinvestment choices (see [Aretz and Pope \(2018\)](#)). Assuming that disinvestment proceeds are shared according to a fixed rule, the model reveals that the distress premium in a class becomes more negative with the proceeds paid out to that class and can be negative in both classes when debtholders receive the lion share but not all of the proceeds. Relying on proxies for the ease with which a firm can disinvest its hard assets, our empirical work supports our theory in showing that the bond and loan distress premiums become more negative with these proxies. Conversely, the stock premium often becomes less negative with them, possibly because shareholders benefit more from the sale of non-secured hard assets.

We use [Campbell et al.’s \(2008\)](#) state-of-the-art distress proxy to show that the distress anomaly arises in stocks, bonds, loans, and firm assets.<sup>2</sup> In our stock-bond sample, our [Fama and MacBeth \(FM\) \(1973\)](#) regressions, for example, show that while the stocks in distress deciles 6-9 earn a 0.24% higher mean monthly return ( $t$ -statistic: 2.61) than the lower-decile stocks, the top-decile stocks earn a 0.61% lower return ( $t$ -statistic: -2.82) than the stocks in deciles 6-9. The corresponding numbers for bonds are -0.06% ( $t$ -statistic: -4.10) and -0.25% ( $t$ -statistic: -4.61), respectively. In our stock-bond-loan-asset sample, the same regressions reveal that while the decile 6-9 loans earn a similar mean monthly return as the lower-decile loans, the top-decile loans earn a 0.46% lower return ( $t$ -statistic: -2.44) than the decile 6-9 loans. Given our evidence of hump-shaped or negative relations between distress

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<sup>2</sup>Many studies suggest that hazard models in general and [Campbell et al.’s \(2008\)](#) logit model in particular are superior in forecasting corporate failures relative to discriminant analysis, structural models, and credit ratings. See [Shumway \(2001\)](#), [Chava and Jarrow \(2004\)](#), [Bharath and Shumway \(2008\)](#), [Campbell et al. \(2008\)](#), and [Hilscher and Wilson \(2017\)](#) for the U.S. and [Aretz et al. \(2018\)](#) for the international evidence. Given that, our evidence corroborates that the negative bond distress premium detected in [Avramov et al. \(2022\)](#) is not an artefact of them using a plausibly weaker and less timely distress proxy.

and returns in the three classes, we unsurprisingly also find a non-positive relation between distress and firm asset returns, the value-weighted average of stock, bond, and loan returns.

Interestingly, while the negative premiums in the stock-bond sample remain significant for about half a year after portfolio formation, those in the stock-bond-loan-asset sample remain significant for only about three months. The reason could be that the stock-bond-loan-asset sample is tilted toward larger firms (as they are more likely to own traded loans), and larger firms are known to produce weaker asset pricing effects ([Fama and French \(2008\)](#)).

We conduct numerous robustness tests to verify our empirical results. In particular, we do not only rely on the month-end-to-month-end bond and loan returns used in most studies but also the alternative returns calculated from the first and last transaction price within a month in [Bartram, Grinblatt, and Nozawa \(2025\)](#). Moreover, we repeat our tests on data excluding matrix prices or reassigning surviving bonds or loans after a merger and acquisition (M&A) deal to the acquiror. While we consistently control for a comprehensive set of factors selected from the recent literature (see, e.g., [Fama and French \(2016\)](#), [Dick-Nielsen, Feldhütter, Pedersen, and Stolborg \(2025\)](#), and [Dickerson, Julliard, and Mueller \(2025\)](#)), we further run separate tests also controlling for the bond illiquidity and bond liquidity risk measures of [Bao, Pan, and Wang \(2011\)](#) and [Lin, Wang, and Wu \(2011\)](#), respectively.<sup>3</sup> Finally, we use Compustat and Capital IQ data to show that while stocks, bonds, and loans capture about 70-75% of the average firm's asset value, trade credit is the one significant omitted liability class, making up about 12-15% of that value.<sup>4</sup> Relying on arguments in [Erens and Hoffmann](#)

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<sup>3</sup>Given that we require daily bond price data to calculate the liquidity proxies, we can only include them in subsample tests over the sample period over which we have such data (July 2002-December 2020).

<sup>4</sup>A second implication is that our asset return calculations underweight loans because, even for firms with

(2013) and Costello (2019) that trade credit is close to risk-free, we rerun our tests on asset returns calculated from stock, bond, loan, and (imputed) trade credit data. All robustness tests yield conclusions in complete agreement with our main empirical specifications.

In our theoretical work, we offer a new rationale for the jointly negative distress premiums in the four asset classes. Our rationale starts from the insight that many firms disinvest real assets in distress. Yet, as the ability to disinvest is akin to a real American put with a negative expected excess return (see Coval and Shumway (2001)), it lowers the expected *asset* return, especially in distress (see Hackbarth and Johnson (2015), Aretz and Pope (2018), and Gu, Hackbarth, and Johnson (2018)). To study if the ability to disinvest can also lower the expected *stock* and *debt* return, we extend the standard real options model of Aretz and Pope (2018) by assuming that the firm is not only financed by stock but also a zero-coupon bond. Critically, we further posit that while the firm funds capacity expansions through equity, it distributes the proceeds from contractions to stock and debt claimants according to some fixed sharing rule. The logic is that the firm's assets consist of easy-to-verify plausibly-tangible secured assets and hard-to-verify plausibly-intangible unsecured assets. While the firm is forced to pay out the proceeds from disinvesting secured assets to debt claimants, it can divert at least some fraction of the proceeds from disinvesting unsecured assets to stock claimants.

Our theoretical results suggest that the extended real options model can produce a negative relation between distress risk and expected stock and/or debt returns if the firm can disinvest its assets at a sufficiently high price. Fixing the disinvestment price, the relation

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traded loans, only a subset of those firms' loans are traded in secondary markets. As a remedy, we also run tests on asset returns calculated based on loan weights adjusted using Capital IQ or Mergent FISD-Compustat data.

between distress risk and the expected return to either claim becomes, in line with intuition, more negative the greater the fraction of disinvestment proceeds paid to that claim. Critically, the model can produce negative relations for both stock and debt when debtholders receive the lion share of disinvestment proceeds and shareholders some small residual.

We finally offer empirical support for the idea that disinvestment options add to the distress anomaly. To that end, we condition the distress premiums in stocks, bonds, and loans on well-known proxies for the ease with which firms are able to disinvest hard assets. More specifically, we rely on (i) [Gu et al.'s \(2018\)](#) asset inflexibility; (ii) [Eisfeldt and Rampini's \(2006\)](#) asset reallocation; (iii) [Schlingemann, Stulz, and Walkling's \(2002\)](#) asset liquidity; and (iv) [Bai, Li, Xue, and Zhang's \(2024\)](#) investment skewness. We first validate these proxies by showing that distressed firms classified as owning more disinvestable hard assets indeed disinvest significantly more than their counterparts. More crucially, they create more negative bond and loan distress premiums, in line with the proceeds from selling such assets flowing (mostly) to debtholders. Strikingly, however, these firms yield a less negative stock premium. The reason may be that more difficult-to-disinvest hard assets are less likely to be used as collateral in debt contracts, allowing firms to channel (or: tunnel) some proceeds from selling those assets to shareholders.

We add to studies on the distress anomaly. [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 proxies, either do not or negatively price stocks. Deriving a distress proxy from [Merton's \(1974\)](#) structural model, [Vassalou and Xing \(2004\)](#) instead find a positive stock distress premium, which is, however, largely driven by

illiquid stocks (see [Da and Gao \(2010\)](#)). Using the alternative structural model proxy of Moody's KMV Corporation, [Garlappi et al. \(2008\)](#) and [Garlappi and Yan \(2011\)](#) find a downward hump-shaped relation between distress and stock returns. Using a distress proxy derived from a hazard model, [Campbell et al. \(2008\)](#) detect a negative stock distress premium. In accordance, [Avramov, Chordia, Jostova, and Philipov \(2009\)](#) find that stock returns are higher for firms with better credit ratings.<sup>5</sup> Closer to us, [Avramov et al. \(2022\)](#) jointly study stocks and bonds, reporting positive premiums for better rated firms in both. We contribute by jointly studying not only stocks and bonds but also loans, allowing us to estimate the firm asset distress premium. We further distinguish ourselves from most studies by using the more recent proxy of [Campbell et al. \(2008\)](#).

We also relate to a literature aiming to explain the distress anomaly. Adding to [Avramov et al. \(2022\)](#), our empirical evidence that distress risk is negatively priced in loans and firm assets casts even greater doubts on [Garlappi et al.'s \(2008\)](#) and [Garlappi and Yan's \(2011\)](#) shareholder advantage theory. The reason is that shareholders are more likely to renegotiate with private (rather than public) debtholders in distress since the Trust Indenture Act requires unanimous consent from all bondholders to modify bond terms. In the same vein, as bond and loan returns both become more negatively (rather than positively) skewed with distress risk, our loan evidence also casts greater doubts on [Conrad et al.'s \(2014\)](#) conjecture that investors' preference for positive skewness drives the distress anomaly. Conversely, our evidence aligns with [O'Doherty's \(2012\)](#) that distressed stocks have low market betas in recessions. While he, however, attributes those betas to uncertainty

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<sup>5</sup>Looking into international data, [Aretz et al. \(2018\)](#), [Eisdorfer, Goyal, and Zhdanov \(2018\)](#), and [Gao, Parsons, and Shen \(2018\)](#) also find a non-positive or negative stock distress premium in non-U.S. stocks.

about the valuation of distressed firms, we would attribute them to disinvestment options. We contribute by proposing a novel rationale for the distress anomaly, also offering empirical evidence directly supporting it.

We finally add to an emerging literature studying loan and firm asset returns. Using stock, bond, and loan data, [Choi \(2013\)](#) shows how firm asset risk helps to explain the stock value premium, while [Choi and Richardson \(2016\)](#) evaluate the pricing of the market beta, market size, book-to-market, and momentum in stocks and firm assets. Different from us, they, however, exploit loan data imputed from only five years of market loan data. Closer to us, [Beyhaghi and Ehsani \(2017\)](#) exclusively consider market loan data to examine the cross-section of loan returns, showing that exposure to [Fama and French's \(1993\)](#) credit risk factor does not robustly price that cross-section. Using structural models to calculate firm asset returns, [Doshi, Jacobs, Kumar, and Rabinovitch \(2019\)](#) establish that the market beta and size (but not book-to-market and volatility) price firm assets. Again relying on imputed loan return data, [Bretscher, Feldhütter, Kane, and Schmid \(2022\)](#) demonstrate that the value (leverage) premium exists in stocks, bonds, and firm asset but not loan returns (only in stock and bond returns). Exclusively using market loan data, we add to these studies by asking how [Campbell et al. \(2008\)](#) distress risk prices loans and firm assets.<sup>6</sup>

We proceed as follows. While Section [II](#) details our variable definitions and data sources, Section [III](#) studies the pricing of distress risk in our asset classes. In Section [IV](#), we show that a real options model with capacity utilization, investment, and disinvestment

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<sup>6</sup>While other studies often rightly defend their usage of imputed loan returns by pointing out that “loans reside toward the top of the capital structure and that their price variations are not particularly large compared with those of the other claims” (see [Choi \(\(2013\), p. 2872\)](#)), we note that this argument may not hold for the loans of highly distressed firms, which are our main focus. Given that, we do not use imputed loan returns.

choices can explain our evidence in Section III. While Section V evaluates our theory's new testable implications, Section VI sums up. We offer more variable details in Appendix A at the end of this paper and theoretical derivations and additional/robustness tests in our Internet Appendix.

## II. Methodology and Data

In this section, we offer variable definitions and describe our data sources. We first outline our two samples, the stock-bond and stock-bond-loan-asset samples, and detail how we calculate returns for each. We next explain how we calculate Campbell et al. (2008) distress risk. We offer additional details about the bond returns, the distress risk predictors used in Campbell et al. (2008), and our control variables in Appendix A at the end of this paper.

### A. The Playing Fields

#### 1. The Stock and Bond Sample

Our stock-bond sample investigates the common stocks (shrcd: 10 and 11) of firms traded on the NYSE, AMEX, and Nasdaq (exchcd: 1, 2, and 3). While we directly source monthly stock returns from CRSP, we replace a stock's return with its delisting return whenever the delisting return is non-missing. If the delisting return is missing but the delisting code available, we replace that return with  $-30\%$  for NYSE and AMEX stocks and  $-55\%$  for Nasdaq stocks (see Shumway (1997) and Shumway and Warther (1999)). We exclude

stocks with a one-month-lagged price below \$5 to mitigate market microstructure issues.

We rely on data from Lehman Brothers' Fixed Income Database, Datastream, the Intercontinental Exchange (ICE), the Trade Reporting and Compliance Engine (TRACE), and Mergent's Fixed Income Securities (FISD) and National Association of Insurance Commissioners (NAIC) databases to compute bond returns and characteristics. While the Lehman Brothers, Datastream, ICE, TRACE, and NAIC databases contain mostly bond market data, the FISD database features bond characteristic data, including the offering amount and date; the maturity date; the coupon rate, type, and frequency; the bond type, rating, and option features; and issuer information. We retrieve Lehman Brothers data over the start-1986 to end-1997 period,<sup>7</sup> Datastream data over the start-1990 to end-2006 period, ICE data from start 1996-to end-2004, NAIC data from start-1994 to end-2020, and TRACE data from July 2002 to end-2020.<sup>8</sup> To align our stock and bond data, we choose the sample period from January 1986 to December 2020 for the stock-bond sample, consisting of 420 monthly observations (35 years).

While we directly source monthly bond returns from the Lehman Brothers database, we calculate the return of bond  $i$  over month  $t$ ,  $r^B$ , from Datastream data as

$RI_{i,t}/RI_{i,t-1} - 1$ , where  $RI$  is the total return index, and  $t$  consistently indicates the entire period for flow (e.g., the return over month  $t$ ) but the end of the period for stock (e.g., the index value at the end of month  $t$ ) variables. We follow [Bessembinder, Kahle, Maxwell, and](#)

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<sup>7</sup>While the Lehman Brothers data start in 1973, they are missing for entire calendar months over the period until start-1986, motivating us to use those data only from start-1986 onward.

<sup>8</sup>In the initial version of our study, we employed only Lehman Brothers, Datastream, TRACE, and NAIC data to calculate bond returns. A disadvantage of that strategy was that we had to resort to mostly Datastream data to calculate those returns from the end of the Lehman Brothers period (end-1997) to the start of the TRACE period (July 2002) because NAIC contains only data on the bond trades of insurance firms. Yet, as Datastream bond data are extremely sparse from 1998 to 2000, we eventually decided to supplement our existing bond data with newly-acquired data from ICE over the 1996-2004 period.

Xu (2009), Choi (2013), and Choi and Richardson (2016) in calculating that return from NAIC, ICE, and TRACE data as:

$$(1) \quad r_{i,t}^B = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1,$$

where  $P$  is the bond price,  $AI$  the accrued interest, and  $C$  the coupon. In case of NAIC and TRACE, we construct  $P_{i,t}$  ( $P_{i,t-1}$ ) from the last five trading days of month  $t$  and, if no transactions occurred over those days, from the first five of month  $t + 1$  (the first five of month  $t$ ). See Appendix A at the end of this paper for more details.

A downside of our main method to calculate returns from NAIC and TRACE data is that if there are no bond transactions over the periods outlined above, the return will automatically be missing. To mitigate that issue, we also follow the alternative methodology of Bartram et al. (BGN) (2025) to create returns. Arguing that, under lenient conditions, the dirty bond price follows a martingale under the physical measure, these authors choose the earliest (latest) dirty price over month  $t$  (month  $t$  plus the first five trading days of month  $t + 1$ ) as proxy for the start (end) month price. They next proceed exactly as in our main methodology.

We impose standard filters on our bond return data. First, we remove non-U.S. bonds. Second, we exclude structured notes; mortgage, asset, or agency-backed bonds; and equity-linked bonds. Third, we remove convertible or puttable bonds. Fourth, we keep only fixed and zero coupon bonds. Fifth, we remove bonds with less than a single year to maturity. Sixth, we exclude bonds with a market capitalization below \$25 million at the start of month  $t$  and returns outside of the  $-100\%$  to  $100\%$  range over that month. Seventh, in case of the

TRACE bond data, we eliminate when-issued and/or locked-in transactions, those with special sales conditions, and cancelled, subsequently corrected, and/or reversed transactions.<sup>9</sup>

While the Lehman Brothers, Datastream, and ICE data contain bond quotes (first two) and/or matrix prices (all three), the NAIC and TRACE data contain transaction prices, with the NAIC data, however, only featuring those associated with the trades of insurance firms. As the consensus opinion is that transaction prices are more reliable than quotes, but that quotes are more reliable than matrix prices, we use the TRACE  $\succ$  NAIC  $\succ$  ICE  $\succ$  Lehman Brothers  $\succ$  Datastream preference order in our bond return calculations.<sup>10</sup> We finally form a value-weighted portfolio of firm  $i$ 's outstanding bonds at the start of month  $t$ . As weight, we use either a bond's market capitalization in case of the Lehman Brothers and Datastream data or the sum of its price and accrued interest times its outstanding number (calculated as the ratio of notional to principle amount) in case of the ICE, NAIC, and TRACE data.

In Section [IA.1](#) of our Internet Appendix, we replicate all the exercises in the appendixes of [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#) to confirm that our bond data are close-to-comprehensive and of a high quality. In particular, we show that although the bond sample is a relatively small (about 15%) subsample of the entire CRSP-Compustat

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<sup>9</sup>We highlight that our sample includes SEC Rule 144A bonds. To mitigate [Choi's \(2013\)](#) and [Choi and Richardson's \(2016\)](#) concern that the registration of these bonds could produce duplicate bonds in our sample, we follow the matching approach of [Han, Huang, Kalimipalli, and Wang \(2022\)](#) to find the dates on which these bonds are registered (if any). We next analyze the change in the outstanding balances of the SEC Rule 144A bonds in Mergent FISD on their registration dates, finding that those balances are reduced to zero or close-to-zero in the vast majority of cases. Manually setting all outstanding balances of the SEC Rule 144A bonds to exactly zero on their registration dates does not materially affect our conclusions. Further excluding other duplicate bonds based on [Han et al.'s \(2022\)](#) matching approach does also not materially change conclusions.

<sup>10</sup>Not everyone agrees. [Kelly and Pruitt \(2022\)](#) write: "Essentially, revealed preference tells us that the ICE pricing data are more accurate because large asset managers pay top dollar to purchase the data."

universe featuring larger and more financially levered firms, it captures on average about 77% of the Compustat book debt of the included firms and about 85% of the outstanding balances in the entire FISD universe. Moreover, the sample contains an only small number of zero-price-change observation (1.70%); both firm and portfolio-level returns constructed from it yield close-to-zero autocorrelations and cross-correlations with one-month-lagged stock returns; and at least the ICE (but not necessarily Datastream) quotes are close to the corresponding NAIC and TRACE transaction prices (mean (median) difference: 0.87% (0.44%)).<sup>11</sup> Given that all these results align with those in the two studies above, we also conclude that our bond sample is reasonably comprehensive and features a small but not major degree of staleness.

## 2. The Stock, Bond, Loan, and Firm Asset Sample

For our stock-bond-loan-asset sample, we obtain data from Creditflux CLO-i, Refinitiv LoanConnector, and Reuters Dealscan to construct loan returns and fundamentals. While CLO-i contains loan transaction data from collateralized loan obligations (CLOs) starting from 2004, LoanConnector contains the bid-ask quotes of main dealers for secondary market loans starting from 1998.<sup>12</sup> Conversely, Dealscan provides loan characteristic data starting from the early 1980s. We use loan identification numbers (LINs) to merge the LoanConnector and Dealscan data. We rely on a matching algorithm based on firm and loan characteristics

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<sup>11</sup>While the corresponding numbers for the Datastream quotes are 2.10% and 0.95%, respectively, their lower quality is less consequential since only 10.5% of our bond-sample prices come from Datastream. Also, we later verify that exclusively using TRACE transaction prices does not change our conclusions.

<sup>12</sup>We stress that our loan data contain trade prices and quotes for both term loans and lines of credit. To be specific, while the vast majority of the CLO-i transaction-price data are for term loans, about 70% (30%) of the LoanConnector quote data are for those same loans (lines of credit). As our data do not include the withdrawn amount for lines of credit, we follow Choi (2013) in assuming that it is equal to 20% of the offering amount. We have verified that variations of that percentage do not materially affect our conclusions.

plus a manual verification to merge the LoanConnector/Dealscan with the CLO-i data.

Following [Choi \(2013\)](#), [Choi and Richardson \(2016\)](#), and [Beyhaghi and Ehsani \(2017\)](#), we calculate the monthly return of loan  $i$  over month  $t$ ,  $r_{i,t}^L$ , as:

$$(2) \quad r_{i,t}^L = \frac{Par_{i,t}P_{i,t} + (Par_{i,t} - Par_{i,t-1}) + AI_{i,t} + C_{i,t}}{Par_{i,t-1}P_{i,t-1} + AI_{i,t-1}} - 1,$$

where  $Par$  is the outstanding par value,  $P$  is the loan price,  $AI$  is the loan accrued interest on a 360-day basis, and  $C$  is the coupon, so that the second summand in the numerator on the right-hand side is the principle repayment over the month.<sup>13</sup> In line with standard data sources, we set  $P_t$  ( $P_{t-1}$ ) to the transaction price on the last (first) trading day of the month if available and else to the bid-ask midpoint. Analogous to bonds, we also use the alternative methodology of BGN to calculate loan returns. As the bid-ask midpoint is, however, almost always available in our data, this strategy only marginally raises our sample size.

Importantly, we highlight that, in contrast to several other studies, we do not impute the loan returns of firms with only non-traded loans from regressions of available loan returns on their corresponding bond returns and Treasury bond returns. We refrain from doing so since the justification for that strategy that loan values are far more stable than stock and bond values due to loans residing at the top of the capital structure is unlikely to hold for the loans of highly distressed firms, which are the main focus of our research.

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<sup>13</sup>We slightly innovate over others in calculating outstanding loan balances. To be specific, we use Dealscan prepayment data to calculate those balances for the about 11% of loans for which these data are available. For the remainder, we distinguish between institutional term loans (term loan B, C, D, etc.), non-institutional term loans (term loan A), and revolving credit. In line with [Standard & Poor's Global Market Intelligence \(2016\)](#), we assume that institutional term loans are entirely repaid on their maturity dates, whereas non-institutional term loans are proportionally repaid over quarters (i.e., are linearly amortized). In agreement with [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#), we assume that the withdrawal rate of revolving credit is 20%.

We impose standard filters on our loan data. First, we drop non-U.S.-syndicated and non-U.S.-dollar loans. Second, we omit loans with less than three months to maturity. Third, we exclude loans with monthly returns outside the  $-100\%$  to  $100\%$  range. We finally again form a value-weighted portfolio of all of firm  $i$ 's outstanding loans at the start of month  $t$ , using a loan's par value times the sum of its price ( $Par \times P$ ) and accrued interest ( $AI$ ) as weight. We omit loan data before August 1999 to ensure wide enough cross-sections. To align our stock and bond (calculated as in Section II.A.1) and loan data, we choose the sample period from August 1999 to April 2020 for the stock-bond-loan-asset sample, featuring 249 monthly observations (around 21 years). Critically, however, we retain a firm-month observation in that sample only if we have stock and loan (but not necessarily bond) data.

Section IA.1 of our Internet Appendix again follows [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#) to evaluate the coverage and quality of our sample loan data. While the loan sample is an even smaller (about 3%) subsample of the CRSP-Compustat universe than the bond sample, it captures on average about 94% of Compustat book debt and about 12% of the outstanding balances in the Dealscan universe. Compared to the bond sample, the loan sample, however, features a much greater number of zero-price-change observations (33.91-vs.-1.70%); the portfolio (but not firm) level loan returns yield a higher first-order autocorrelation (0.43-vs.-0.10); and the firm-level returns share a higher cross-correlation with one-month-lagged stock returns (0.15-vs.-0.06). Notwithstanding, as stressed by [Choi and Richardson \(2016\)](#), the high proportion of zero-price-change observations may not indicate price staleness but rather stable expectations about interest rates and default risk. Also, the loan quotes are close to their corresponding transaction prices (mean (median) difference: 1.85% (0.51%)), and the

cross-correlation of 0.15 implies an R-squared of only about 2% in a regression of loan returns on one-month-lagged stock returns. Overall, we thus conclude that while our loan sample prices are more stale than our bond sample prices, the overall level of staleness is arguably still non-severe.

We next follow [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#) in appealing to [Modigliani and Miller's \(1958\)](#) insight that the value of a firm's real assets equals the value of its financial assets and approximate the firm's (real) asset return as the value-weighted average of its stock, value-weighted bond-portfolio, and value-weighted loan-portfolio returns. To avoid bias arising from those bonds and loans excluded by our filters, we also include them in our calculations, assuming, however, that their returns equal those of their non-excluded counterparts. In particular, let  $E$  be a firm's stock market capitalization,  $B$  the sum of bond price plus accrued interest ( $P + AI$ ) times number of bonds outstanding taken over all its included and excluded bonds, and  $L$  the sum of par value times price plus accrued interest ( $Par \times P + AI$ ) taken over all its included and excluded loans. Letting  $MV$  be the sum of  $E$ ,  $B$ , and  $L$ , we then approximate firm  $i$ 's asset return over month  $t$ ,  $r^A$ , as:

$$(3) \quad r_{i,t}^A = \left( \frac{E_{i,t-1}}{MV_{i,t-1}} \right) r_{i,t}^S + \left( \frac{B_{i,t-1}}{MV_{i,t-1}} \right) r_{i,t}^{BP} + \left( \frac{L_{i,t-1}}{MV_{i,t-1}} \right) r_{i,t}^{LP},$$

where  $r^S$  and  $r^{BP}$  are the stock and value-weighted bond return calculated as in [Section II.A.1](#), respectively, and  $r^{LP}$  the value-weighted loan return calculated as in this section.

We acknowledge that our asset return proxy is imperfect because it ignores (i) non-traded loans held by even those firms with traded loans and (ii) non-traded liabilities. We later run robustness test showing that these imperfections do not greatly distort our

conclusions.

## B. The Pricing Variable: Corporate Distress Risk

We use [Campbell et al.’s \(2008\)](#) logit-hazard model to capture twelve-month-ahead firm distress risk with only data available to investors at the time. To do so, we estimate a logit model of a dummy variable set to one if a firm defaults, files for bankruptcy, or delists for performance reasons over the month twelve months from the current and else zero, *Failure*, on distress predictors at the end of the current month. We can compactly write that model as:

$$(4) \quad \text{Prob}(Failure_{i,t} = 1 | \mathbf{X}_{i,t-12}) = \frac{1}{1 + \exp(-\alpha - \beta \mathbf{X}_{i,t-12})},$$

where  $\alpha$  is a parameter,  $\beta$  is a vector of parameters, and  $\mathbf{X}$  is a vector encompassing the distress predictors. Consistent with [Campbell et al. \(2008\)](#), we estimate model (4) recursively, using data from start-January 1963 to end-December of calendar year  $t$ , where  $t$  ranges from 1980 to 2008 in unit increments. We next combine the estimates from the estimation window stretching to the end of calendar year  $t$  with the distress predictor values over calendar year  $t + 1$ . See [Appendix A](#) for more details about the default risk predictors.

We obtain the stock and accounting data required to compute the distress proxy from CRSP and Compustat. Yet, since we do not have access to [Campbell et al.’s \(2008\)](#) failure data, we cannot estimate logit model (4) ourselves. Fortunately, Jens Hilscher sent us the output from recursively estimating that model starting from 1980. We use the output

obtained from his longest window, 1963-2008, to calculate the distress proxy for the post-2008 period. Doing so is unproblematic as his estimates strongly converge over time.<sup>14</sup>

## C. The Control Variables

We use a comprehensive set of controls in our portfolio sorts and FM regressions. In our portfolio sorts, we always start from simple factor models but then gradually expand these. In our stock sorts, we, for example, start from the [Fama and French \(FF3S\) \(1993\)](#) three-factor model featuring the MKT, SMB, and HML. We next move to the [Fama and French \(FF5S\) \(2015\)](#) five-factor model by adding RMW and CMA and then to the [Fama and French \(FF6S\) \(2016\)](#) six-factor model by further adding MOM. Conversely, in our bond and loan sorts, we start from the [Fama and French \(FF5SB\) \(1993\)](#) five-factor model featuring the MKT, SMB, HML, DEF, and TERM. We next move to an eight-factor model by adding an investment and a speculative-grade bond portfolio and bond momentum (SB8). We finally also add a parsimonious selection of bond factors chosen from recent bond pricing studies, as, for example, [Dick-Nielsen et al. \(2025\)](#) and [Dickerson et al. \(2025\)](#), and including bond value, short and long-term reversal, duration, and carry factors and the firm earnings announcement drift (SB14).<sup>15</sup> In our FM regressions, we use a comprehensive set of stock, bond, loan, and firm characteristics known to price our asset classes. See [Appendix A](#) at the end of this paper for more details about our choice of controls and how we calculate them.

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<sup>14</sup>We thank Jens Hilscher and his co-authors for sharing the output from their estimations.

<sup>15</sup>While the only factor model used in the literature to price loans is the FF5SB model (see [Beyhaghi and Ehsani \(2017\)](#)), both bonds and loans are debt. The upshot is that the same (or at least similar) factors plausibly price those two asset classes. Given that, we also use the SB8 and SB14 factor models to price loans.

### III. The Pricing of Corporate Distress Risk

In this section, we investigate the pricing of corporate distress risk. We first offer descriptive statistics. We next study the pricing of distress risk first in our stock-bond and then our stock-bond-loan-asset sample. We finally present robustness test results.

#### A. Descriptive Statistics

Table 1 offers descriptive statistics for our sample data. Panels A and B focus on the stock-bond and the stock-bond-loan-asset sample, respectively. The descriptive statistics include the number of observations (Obs), the mean, the standard deviation, and the first, 25th, 50th, 75th, and 99th percentiles, computed by sample month and then averaged over time. Panel A shows that the stock-bond sample contains an average of 3,480 stocks and between 764 (standard return) and 779 (BGN return) bond portfolios per month. Also, stocks attract both a higher monthly mean return (1.01% vs. 0.71%)<sup>16</sup> and standard deviation (12.27% vs. 2.33%) than bonds, and the average stock is larger than the average bond capitalization (\$3.86 vs. \$2.23 billion). Lastly, the average bond of the average sample firm has a bond market beta of 0.58, a time-to-maturity of about ten years, and a credit rating close to BBB.

**Insert Table 1 Here.**

In contrast, Panel B reveals that the stock-bond-loan-asset sample contains an average of only 179 (standard return) or 186 (BGN return) firms per month because few

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<sup>16</sup>We consistently use excess returns (i.e., raw return minus risk-free rate) in our empirical work.

firms own loans traded in secondary markets.<sup>17</sup> Contrasting stock and bond capitalizations across the samples, the stock-bond-loan-asset sample is heavily tilted toward larger firms. In line with the stock-bond sample, stocks have higher mean monthly returns (0.77% vs. 0.65%) and standard deviations (14.28% vs. 4.24%) than bonds, while bonds have higher mean returns (0.65% vs. 0.30%) and standard deviations (4.24% vs. 2.13%) than loans. Next, the average bond of the average sample firm has a lower bond market beta of 0.45, a shorter time-to-maturity of about seven years, and a lower rating around B+ relative to the stock-bond sample. Conversely, the average loan of that firm has a market size of \$0.80 billion and a time-to-maturity of about four years. Finally, the mean monthly asset return of about 0.54% lies between the mean monthly stock, bond, and loan returns (0.77%, 0.65%, and 0.30%, respectively).

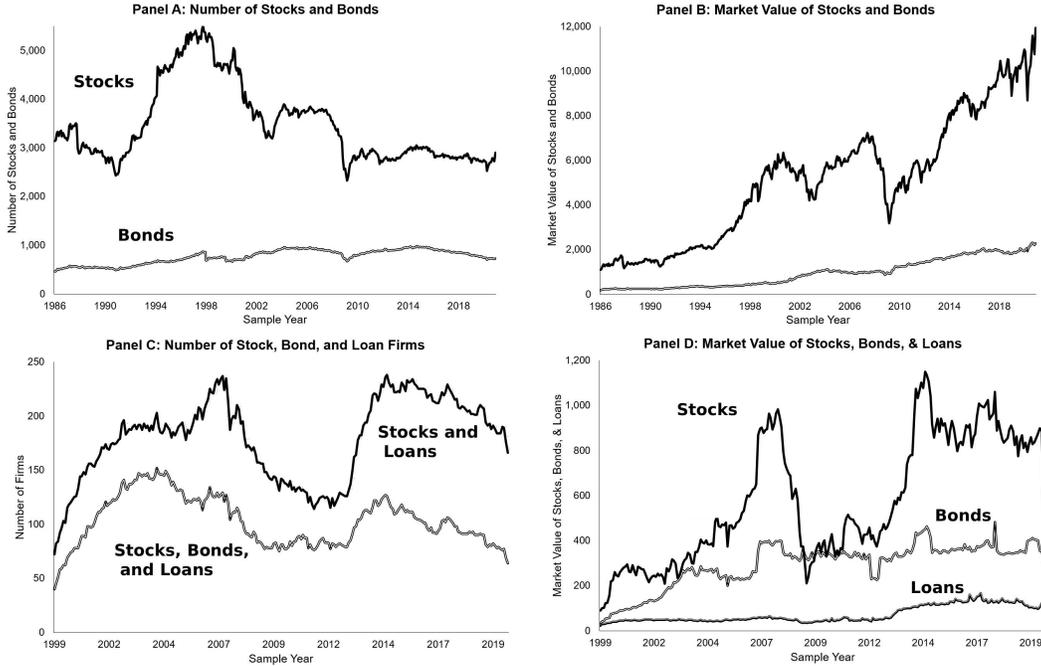
Figure 1 plots the numbers and aggregate capitalizations of the asset classes in our stock-bond (Panels A-B) and stock-bond-loan-asset (Panels C-D) samples, respectively. While Panel A shows that the stock-bond sample contains between about 2,300 to 5,500 stocks and between about 460 to 980 (firm-specific) bond portfolios, Panel B reveals that bonds make up between 10-20% of the aggregate stock-and-bond capitalization. Panel C suggests that the stock-bond-loan-asset sample contains between about 70 to 240 (40 to 152) firms with stocks and loans (stocks, bonds, and loans), representing only 2-8% of the stock-bond sample. Finally, Panel D shows that the aggregate capitalization and its corresponding volatility is markedly higher for stocks than bonds, but then also markedly

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<sup>17</sup>Given our claim that the BGN methodology matters less for loans than bonds since loan quotes are almost always available (recall Section III.A.2), it may be surprising that it raises the loan sample size more than the bond sample size. The reason, however, is that when we cannot compute a standard bond return from TRACE data, we can often still compute it from Datastream or ICE data, mitigating issues associated with missing transaction prices at the start or end of the month. In contrast, when we cannot compute a standard loan return from CLO-i or LoanConnector data, we have access to no other databases to compute it.

**Figure 1: Sample Composition**

The figure plots the numbers and aggregate market capitalizations of the asset classes in our empirical work over our sample periods. While Panel A (B) shows the number of firms with stocks or bonds (the aggregate stock and bond capitalizations) in the stock-bond sample, Panel C (D) reports the number of firms with stocks and loans or stocks, bonds, and loans (the aggregate stock, bond, and loan capitalizations) in the stock-bond-loan-asset sample.



higher for bonds than loans.

## B. The Stock and Bond Sample

We next study the pricing of corporate distress in the stock-bond sample. We start with sorting our sample stocks or firm-specific bond portfolios into portfolios according to the decile breakpoints of [Campbell et al.'s \(2008\)](#) distress proxy at the end of month  $t - 1$ . We either value or equally weight the portfolios, where we use a firm's stock capitalization or its aggregate bond capitalization to calculate the value weights. We hold the portfolios over month  $t$ . For each set of portfolios, we create three spread portfolios to identify non-linearities in the mean return-distress relation. While the first is long the middle (i.e.,

fifth) distress portfolio and short the bottom (“Middle–Low”), the second is long the top and short the middle (“High–Middle”) and the third long the top and short the bottom (“High–Low”). We risk-adjust by computing the intercept (“alpha”) from regressing portfolio excess returns on the factors of the models in Section III.C.

Table 2 gives the portfolio sort results. While Panel A focuses on the stock and Panel B on the (firm-specific) bond portfolios, subpanels B.1 and B.2 in Panel B report the spread portfolio results calculated from standard and BGN returns, respectively. While column 1 shows mean Campbell et al. (2008) distress risk, columns 2 to 5 (6 to 9) present the mean monthly returns and alphas of the value (equally) weighted portfolios (all in %). Plain numbers are estimates, whereas those in square brackets are Newey-West (1987)  $t$ -statistics with a twelve-month lag length. Panel A suggests that, in line with the literature, mean stock returns and alphas are hump-shaped in distress risk, with them mildly rising over the first eight deciles but sharply dropping over the last two. The value-weighted alpha of the most comprehensive factor model, the FF6S alpha, for example, rises mildly by 0.14% ( $t$ -statistic: 0.89) over the first five deciles but then drops sharply by 1.12% ( $t$ -statistic:  $-2.89$ ) over the final five (see column 5). As a result, the drop in that alpha over the entire set of deciles is a less pronounced but still moderately significant  $-0.98\%$  ( $t$ -statistic:  $-2.25$ ).

**Insert Table 2 Here.**

Panel B shows that mean bond returns and alphas decline more monotonically with distress risk, although the starkest drops again occur over the final deciles. The value-weighted standard-return alpha of the most comprehensive factor model, the SB14 alpha, for example, drops mildly by 0.06% ( $t$ -statistic:  $-2.06$ ) over the first five deciles but

more sharply by 0.41% ( $t$ -statistic:  $-6.16$ ) over the final five (see column 5 in Panel B.1). Thus, the drop in that alpha over the entire set of deciles is an even stronger and more significant  $-0.47\%$  ( $t$ -statistic:  $-7.51$ ). Contrasting the standard and BGN return results in subpanels B.1 and B.2 reveals them to be close-to-identical, mostly due to the great overlap between the samples.

Table IA.4 and Figure IA.3 in the Internet Appendix report the mean characteristics and the factor loadings of the portfolios in Table 2, respectively. Both suggest that high-distress stocks tend to be small, unprofitable value stocks with high market betas, as also reported in prior studies. Conversely, high-distress bonds tend to be small, illiquid bonds with high speculative-grade bond market betas and coupon rates but low ratings and past returns. They also load more negatively on the earnings announcement factor than safer bonds.

In Table 3, we supplement our portfolio sorts with FM regressions explaining the month- $t$  return. We run those regressions on the full stock sample in column 1 and the subsample of stocks with outstanding bonds in columns 2 and 3. Conversely, we run them on the full bond sample, the subsample of investment grade bonds, and the subsample of speculative grade bonds in columns 4 to 6, 7, and 8, respectively. We define as investment (speculative) grade bonds the value-weighted portfolio of all of a firm's bonds with a rating equal to or above (below) BBB- at the start of month  $t$ . To capture non-linearities, we use as main regressors two dummy variables calculated from our distress proxy, the first (second), *HighDistress* (*LowDistress*), set to one if the distress proxy takes on a value within the top decile (below the median) at the end of month  $t - 1$  and else zero. In columns 3 and 5, we

interact the distress dummies with a dummy variable set to one if the return of the other asset class is below the first quartile and else zero,  $LowS/BRet$ . We further add the controls referred to in Section III.C. As always, plain numbers are monthly premium estimates (in %), whereas those in square brackets are Newey-West (1987)  $t$ -statistics with a twelve-month lag.

**Insert Table 3 Here.**

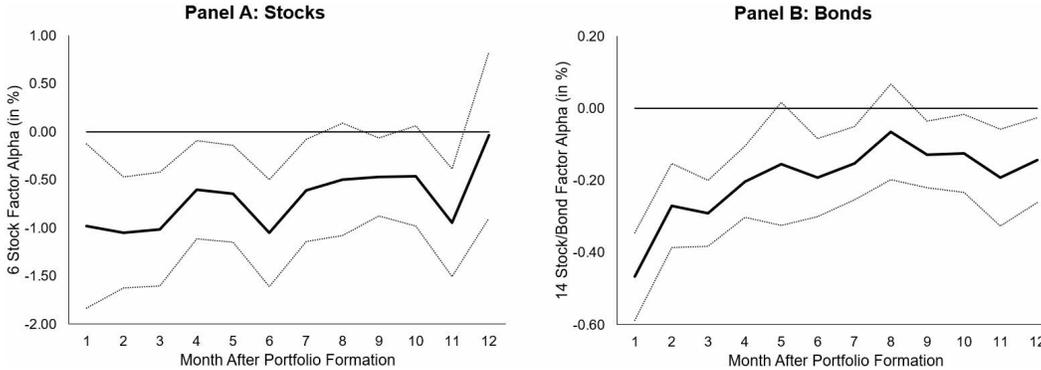
The FM regressions support our portfolio sorts by corroborating that mean stock returns are hump-shaped in distress risk but that mean bond returns decline more monotonically with it. Starting with the full stock sample, column 1, for example, shows that while the stocks in distress deciles 6-9 earn a 0.24% ( $t$ -statistic: 2.61) higher mean return than those in deciles 1-5, the top-decile stocks earn a 0.61% ( $t$ -statistic: -2.82) lower mean return than the decile 6-9 stocks. Conversely, column 4 reveals that the corresponding numbers for the full bond sample are -0.06% ( $t$ -statistic: -4.10) and 0.25% ( $t$ -statistic: -4.61), respectively. Noteworthily, column 2 suggests that the stocks-with-bonds subsample also produces a hump-shaped mean stock return-distress relation and columns 7 and 8 that the negative mean bond return-distress relation amplifies in the speculative-grade bond subsample.<sup>18</sup> In addition, the regressions featuring interactions with the other asset class in columns 3 and 5 suggest that distressed stocks (bonds) are more likely to underperform if the corresponding bonds (stocks) do so, too, refuting that one asset class exploits the other (as in the shareholder advantage theory). Finally, the standard and BGN returns again yield

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<sup>18</sup>The subsample regressions offer some first evidence that the negative relation between bond returns and Campbell et al. (2008) distress risk is not driven by Avramov et al.'s (2022) finding that those returns are also higher for bonds with better credit ratings. To dig deeper into that possibility, we also ran a dependent portfolio sort, sorting our sample bonds first into rating and then distress portfolios or vice versa. Internet Appendix Table IA.6 reveals that while SB14 bond alphas still significantly decline with distress risk within each rating portfolio, they are either higher or statistically similar for worse-rated bonds within each distress portfolio.

## Figure 2: The Longer-Horizon Stock and Bond Distress Premiums

The figure plots the monthly FF6S stock (Panel A) and SB14 bond (Panel B) alpha of the value-weighted high-minus-low distress decile spread portfolio (solid line) and the corresponding 95% confidence bands (broken lines) separately for each of the first twelve months after portfolio formation (i.e., months  $t$  to  $t + 11$ ) in the stock-bond sample.



close-to-identical results, and the stock and bond controls produce premiums in agreement with the literature.<sup>19</sup>

In Figure 2 and Table IA.5 in the Internet Appendix, we investigate the persistence in the stock and bond distress premiums in the stock-bond sample. Specifically, the figure plots the monthly FF6S stock (Panel A) and SB14 bond (Panel B) alphas of the value-weighted high-minus-low distress decile spread portfolios formed at the end of month  $t - 1$  plus their corresponding 95% confidence bands separately for each month from  $t$  to  $t + 11$ . The table offers the same results plus the corresponding results from the equivalent equally-weighted spread portfolios and FM regressions. The figure and table suggest that the stock and bond distress premiums dissipate only slowly over time, with them being statistically significant at the 95% level or better for about half a year after portfolio formation.

<sup>19</sup>The insignificant market beta, market size, and book-to-market premiums in stock returns agree with Fama and French's (1992) (2021) and Horowitz, Loughran, and Savin's (2000) evidence that those premiums have disappeared over recent periods. Conversely, the significant momentum, asset growth, and profitability premiums agree with Fama and French's (2015) (2016) evidence that those premiums still exist over those periods.

## C. The Stock, Bond, Loan, and Firm Asset Sample

We now study the pricing of corporate distress risk in the stock-bond-loan-asset sample. We again start with separately sorting our sample stocks, firm-specific bond portfolios, firm-specific loan portfolios, and firm-asset portfolios into portfolios according to the quintile breakpoints of [Campbell et al.’s \(2008\)](#) distress proxy at the end of month  $t - 1$ . We rely on quintile rather than decile breakpoints because the stock-bond-loan-asset sample is much smaller than the stock-bond sample due to it featuring only those firms with stocks and traded loans. The implication is that decile breakpoints sometimes yield ill-diversified portfolios. We again value or equally weight the portfolios and hold them over month  $t$ . Consistent with the prior section, we form three spread portfolios to identify non-linearities in the mean return-distress relations, the first (second) [third] long the middle (top) [top] and short the bottom (middle) [bottom] portfolio (“Middle–Low,” “High–Middle,” and “High–Low,” respectively). We again risk-adjust by regressing excess portfolio returns on the factors of the same models as before.

Using a design analogous to [Table 2](#), [Table 4](#) gives the results from the portfolio sorts, with Panels A to C focusing on stocks, bonds, and loans, respectively. Panels A and B confirm that mean stock returns are hump-shaped in distress risk, while mean bond returns drop more monotonically with it. The value-weighted FF6S stock alpha, for example, rises by 0.46% ( $t$ -statistic: 1.53) over the initial three quintiles but sharply drops by 1.58% ( $t$ -statistic:  $-3.10$ ) over the final three. The overall change is thus  $-1.12\%$  ( $t$ -statistic:  $-2.49$ ). Conversely, the value-weighted standard-return SB14 bond alpha stays virtually constant over the initial three quintiles but sharply drops by 0.88% ( $t$ -statistic:  $-3.58$ ) over the final three. The overall

change is thus  $-0.87\%$  ( $t$ -statistic:  $-3.52$ ). Interestingly, Panel C suggests that traded loans are similar to bonds since their mean returns also drop monotonically with distress risk. The value-weighted standard-return SB14 loan alpha, for example, drops by  $0.06\%$  ( $t$ -statistic:  $-1.88$ ) over the initial three quintiles and  $0.30\%$  ( $t$ -statistic:  $-2.66$ ) over the final three. The overall change is thus  $-0.36\%$  ( $t$ -statistic:  $-2.89$ ). The similar patterns for bonds and loans come as no surprise since both asset classes represent debt claims. Just like before, our inferences are close-to-identical across the standard and the BGN (bond or loan) return samples.

**Insert Table 4 Here.**

Table 5 offers the results from the portfolio sorts on firm assets, calculated as the value-weighted combination of stocks, bonds, and loans (recall equation (3)). The table shows that, similar to stocks, mean firm-asset returns are hump-shaped in distress risk, although the hump is less pronounced than for stocks. The value-weighted standard-return SB17 firm-asset alpha, for example, rises by  $0.11\%$  ( $t$ -statistic:  $0.50$ ) over the initial three quintiles but drops sharply by  $0.91\%$  ( $t$ -statistic:  $-3.59$ ) over the final three. The overall change is thus  $-0.80\%$  ( $t$ -statistic:  $-2.64$ ). The similarity between the stock and firm asset results is largely due to (i) the greater variations in mean stock relative to mean bond or loan returns over the quintiles, and (ii) the greater weights associated with stocks than bonds or loans.

**Insert Table 5 Here.**

Internet Appendix Table IA.7 and Figure IA.4 present the mean characteristics and factor loadings of the portfolios in Tables 4 and 5, respectively. While both corroborate that

the characteristics and loadings of the stock and bond portfolios largely agree across the stock-bond and the stock-bond-loan-asset sample, they further reveal that high-distress loans are short-maturity loans with low (i.e., negative) loadings on the default spread, the term spread, and the earnings announcement factors. Moreover, high-distress firm assets also command low loadings on the default spread and term spread factors, but, interestingly, high loadings on the speculative-grade bond market portfolio and the bond value (HML) factor.

**Insert Table 6 Here.**

Using a design identical to Table 3, Table 6 once again supplements our portfolio sorts with FM regressions. The table confirms the relations of mean stock, bond, and loan returns with distress risk suggested by the portfolio sorts. While the stocks in distress deciles 6-9, for example, earn a 0.11% ( $t$ -statistic: 0.37) higher mean return than lower-decile stocks, the top-decile stocks earn a 1.06% ( $t$ -statistic: -2.23) lower mean return than decile 6-9 stocks (see column 1). Notwithstanding, the regressions yield more monotonically negative mean firm-asset return-distress risk relations. While the firm assets in distress decile 6-9, for example, earn a 0.02% ( $t$ -statistic: -0.12) lower standard mean return than lower-decile assets, the top-decile firm assets earn a 0.79% ( $t$ -statistic: -3.21) lower mean return than the decile 6-9 assets (see column 9). Similar to before, distressed stocks, bonds, or loans are more likely to underperform if the other asset classes do so, too, although the modulating effect is not always significant (see columns 2, 4, and 7). Finally, the standard and BGN returns again yield close-to-identical results, whereas most controls, however, do not produce significant premiums, likely due to the stock-bond-loan-asset sample's tilt toward larger firms.

### Figure 3: The Longer-Horizon Stock, Bond, Loan, and Firm-Asset Distress Premiums

The figure plots the monthly FF6S stock (Panel A), SB14 bond (Panel B), SB14 loan (Panel C), and SB17 firm-asset (Panel D) alpha of the value-weighted high-minus-low distress quintile spread portfolio (sold line) and the corresponding 95% confidence bands (broken lines) separately for each of the first twelve months after portfolio formation (i.e., months  $t$  to  $t + 11$ ) in the stock-bond-loan-asset sample.

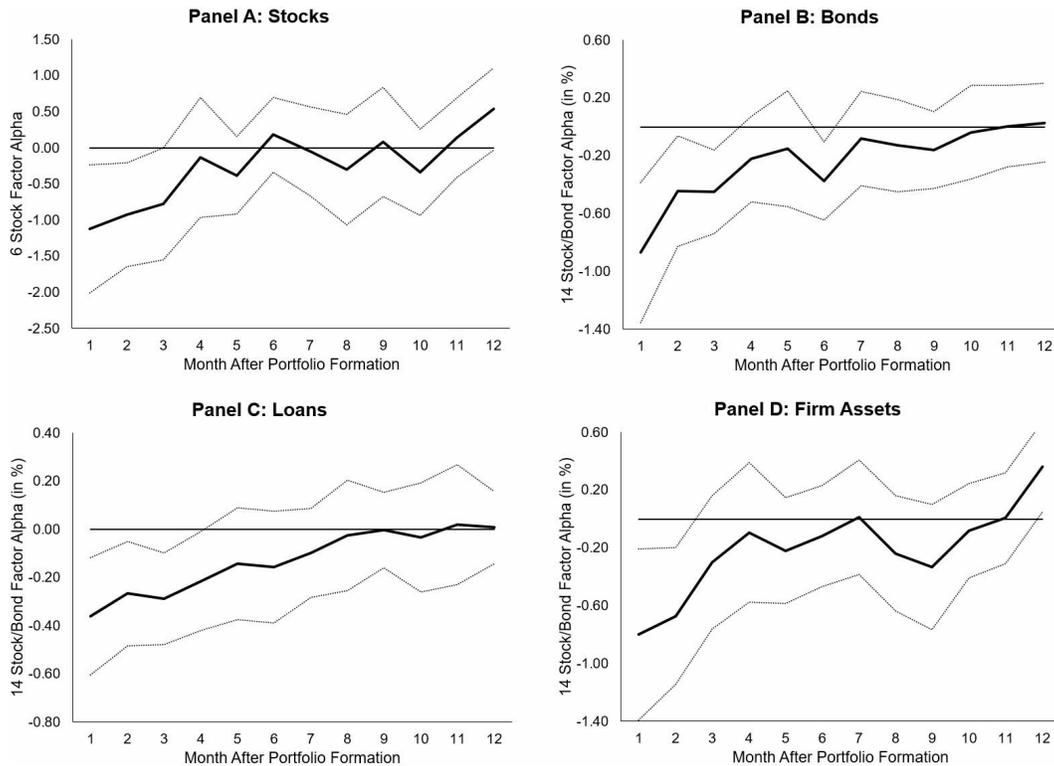


Figure 3 and Table IA.8 in the Internet Appendix study the persistence of the stock, bond, loan, and firm-asset distress premiums in the stock-bond-loan-asset sample. In particular, the figure plots the monthly FF6S stock (Panel A), SB14 bond (Panel B), SB14 loan (Panel C), and SB17 firm-asset (Panel D) alphas of the value-weighted distress quintile spread portfolios plus their corresponding 95% confidence bands separately for months  $t$  to  $t + 11$ . The table offers the same results plus those from the equivalent equally-weighted portfolios and FM regressions. Both reveal that the stock and firm-asset premiums remain significant for about 2-3 months, the bond premium for about 1-4 months, and the loan premium for about 3-4 months. The weaker persistence in the stock-bond-loan-asset sample

is likely due to its skew toward larger firms known to produce weaker anomalies ([Fama and French \(2008\)](#)).

## **D. Robustness Tests**

In this section, we briefly summarize the results from several robustness tests, offering more details plus the corresponding tables and figures in our Internet Appendix.

### **1. The Effects of Matrix Prices**

A concern about our empirical work could be that our bond sample features returns computed from Lehman Brothers, Datastream, and ICE matrix prices, which may be stale and of a notoriously poor quality. To mitigate that concern, we repeat all portfolio sorts and FM regressions exclusively using bond transaction prices from TRACE over the TRACE sample period from July 2002 to December 2020. Doing so, we also examine whether our conclusions continue to hold over a more recent sample period. Internet Appendix Tables [IA.9](#) to [IA.12](#) suggest that matrix prices and our sample period do not materially affect our conclusions.

### **2. The Effects of Illiquidity and Liquidity Risk**

Another concern could be that we do not control for bond illiquidity and liquidity risk in our main tests, especially since these variables are known to price bonds (see [Bao et al. \(2011\)](#) and [Lin et al. \(2011\)](#)) and plausibly correlated with distress risk. Our main reason for not doing so is that we require daily bond data to compute the popular proxies for these

variables advocated in the two studies. Relying on daily TRACE transaction prices to compute the proxies, Internet Appendix Tables [IA.9](#) to [IA.12](#) show that our portfolio sort and FM regression results are robust to controlling for them over the TRACE sample period.

### **3. The Effects of Changes in Bond or Loan Ownership After M&A Deals**

Yet another concern may be that we rely on mappings linking our sample bonds and loans to firms not capturing changes of bond or loan ownership triggered by M&A deals. In particular, our bond mapping uses the company ticker as main firm identifier but only keeps the bond-firm link with the longest duration to mitigate the effects of non-synchronicities in the updating of tickers in the bond and firm data.<sup>20</sup> Conversely, the loan mapping matches loans and firms only on the loan origination date. To address these issues, we follow [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#) in using the CRSP event file to identify the acquirors and targets in all M&A deals (excluding asset acquisitions) from start-1986 plus the corresponding M&A dates. We next reassign the bonds and loans of targets to their acquirors if those instruments continue to be traded for at least a year after the deal date. Internet Appendix Tables [IA.13](#) to [IA.16](#) show that this modification does not materially alter our conclusions.

### **4. The Effects of Non-Traded and/or Underrepresented Liabilities**

A final concern could be that equation (3) is a poor approximation of true asset returns, possibly due to it omitting important non-traded liabilities and/or it abstracting

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<sup>20</sup>We use the WRDS CRSP-TRACE and Christian Stolborg's link files to merge bonds and firms over the TRACE and pre-TRACE sample period, respectively. We thank the Wharton Research Data Services (WRDS) support team for outlining the major issues associated with their linking strategy to us.

from the non-traded loans held by even those firms with traded loans. In Internet Appendix Tables [IA.17](#) and [IA.18](#) and Figure [IA.5](#), we use Compustat and Capital IQ data to look deeper into that concern, evaluating the financing structure of our sample firms. Noticing that trade credit is the only important non-traded liability, we rely on arguments in [Erens and Hoffmann \(2013\)](#) and [Costello \(2019\)](#) suggesting that trade credit is plausibly risk-free to include it in our asset returns. We also use Capital IQ or Mergent FISD/Compustat data to adjust the loan weight in those returns. Internet Appendix Tables [IA.19](#) and [IA.20](#) show that adjusting for trade credit and/or non-traded loans does not materially change our conclusions.

Taken together, this section shows that distress risk is not only hump-shaped or negatively related to stock and bond but also loan and firm asset returns. Interestingly, however, the tendency of distressed firms to underperform is positively correlated across asset classes. The upshot is that our evidence does not suggest that redistribution effects between classes explain the distress anomaly, as, for example, posited by the shareholder advantage theory.

## **IV. A Disinvestment Rationale for the Distress**

### **Anomaly**

In this section, we offer an explanation for the jointly negative distress premiums in stocks, bonds, loans, and firm assets in Section [III](#). We first outline the main premise of our explanation. We next develop a real options model of a stock-and-debt financed firm making

capacity utilization, investment, and disinvestment decisions. We finally reveal that the model can produce (i) a negative stock (debt) distress premium if disinvestment proceeds are high and a sufficient fraction of those flow to stock (debt) claimants and (ii) jointly negative premiums if those proceeds are high and debt claimants reap the lion share but not all of them.<sup>21</sup>

## A. The Main Premise of Our Disinvestment Rationale

Our explanation starts from noting that distressed firms often sell their real assets (see Ofek (1993), Asquith, Gertner, and Scharfstein (1994), and Brown, James, and Mooradian (1994)). Yet, as the ability to sell a real asset is akin to an American put option, and since puts have negative expected excess returns (Coval and Shumway (2001)), such options lower the firm’s expected *asset* return, especially in distress (see Hackbarth and Johnson (2015) and Aretz and Pope (2018)). Our contribution is to show that those options are also able to lower the firm’s expected *stock* or *debt* return in distress if a sufficient amount of disinvestment proceeds flows to the appropriate claimants.

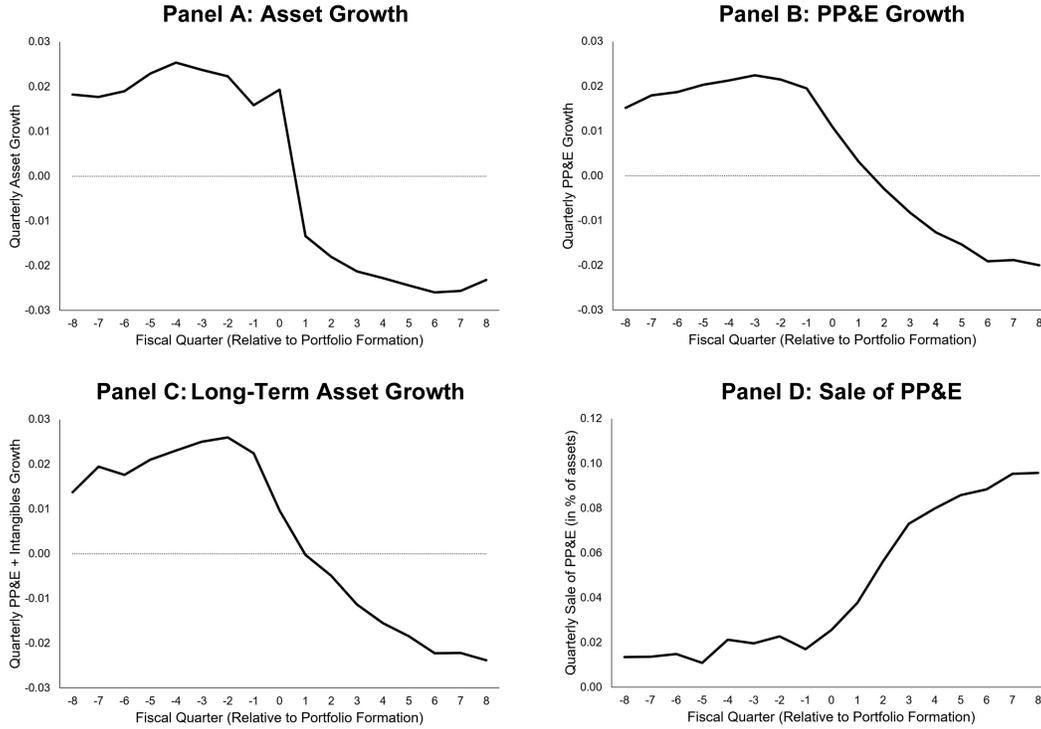
Figure 4 corroborates that our sample distressed firms also sell off their real assets. To create the figure, we select only the top-distress-decile firms from the stock-bond sample in Section IV.B and compute their quarterly asset (Panel A), property, plant, and equipment (PP&E; Panel B), and long-term asset (Panel C) growth and their sales of PP&E (Panel D)

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<sup>21</sup>In Section IA.6 of the Internet Appendix, we further study Fan and Sundaresan’s (2000) real options model of a stock-and-debt financed firm in which shareholders can strategically default. We do so to show that while a higher shareholder advantage is able to produce a more negative stock distress premium, it is unable to produce a negative debt distress premium. The upshot is that Garlappi et al.’s (2008) and Garlappi and Yan’s (2011) shareholder advantage theory does not align with the negative debt distress premiums in our empirical work. We do not report these results in this section since many readers found them “too obvious.”

**Figure 4: The Capacity Disinvestments of Distressed Firms**

The figure plots the mean asset (Panel A), net property, plant, and equipment (Panel B), and net property, plant, and equipment plus long-term intangibles (Panel C) growth and the mean proceeds from sales of property, plant, and equipment scaled by assets (Panel D) of the top distress decile firms in our stock-bond portfolio sort over the 16 quarters surrounding the quarter containing the portfolio formation date. We first average by cross-section and then over our sample period. We use Kenneth French's 49 industry scheme to adjust for industry heterogeneity.



for the 16 quarters surrounding the portfolio-formation-month quarter (see the figure caption for variable definitions). To adjust for industry heterogeneity, we demean at the 49 Fama-French industry classification-quarter level. We finally take cross-sectional and then time-series averages. The figure reveals that our stock-bond-sample distressed firms start selling off their real assets starting from about the portfolio formation quarter (i.e., quarter 0).

## B. A Real Options Model of a Stock-and-Debt Financed Firm

We study a stock-and-debt financed firm operating in continuous time  $t \in [0, \infty)$ . The firm owns a continuum of incremental options to produce a unique output good (“assets-in-place”) and options to install more of those incremental options (“growth options”). Starting with the firm’s production choices, let us index the incremental options by  $k \in [0, \infty)$ , with the  $k^{th}$  option written on the  $k^{th}$  output increment, and assume that the firm owns the options to produce up to the  $K^{th}$  output increment (so  $K$  is the firm’s installed capacity). In each instant, the firm can switch on or off each option to produce, where switching on or off is cost-free. When switched on, the  $k^{th}$  option produces one output increment per time unit at a unit cost of  $C(k) = c_1 + c_2k + f$ , where  $c_1$  and  $c_2$  are the variable cost parameters and  $f$  the fixed cost parameter. When switched off, it does not produce output but still incurs a unit cost of  $C(k) = f$ . We finally assume that the firm instantaneously sells its output at the stochastic price  $\theta$ , which is governed by the geometric Brownian motion (GBM):

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

where  $\mu$  is the total expected return,  $\delta$  the dividend yield, and  $\sigma$  the volatility of a mimicking portfolio tracking variations in the output price, and  $W$  is a Brownian motion.

Our assumptions imply that the firm optimally switches on the option to produce the  $k^{th}$  output increment in the current instant if  $\theta \geq c_1 + c_2k$ . In turn, it sets its output quantity,  $Q$ , to  $\min(Q^*, K)$ , where  $Q^*$  is the optimal quantity to produce if the firm’s

installed capacity were infinite. Given  $Q$ , the firm's profits per time unit,  $\Pi$ , are equal to:

$$(6) \quad \Pi = \int_0^Q (\theta - c_1 - c_2k) dk - fK = \theta Q - c_1Q - \frac{1}{2}c_2Q^2 - fK,$$

and the firm immediately distributes those profits to its shareholders.

We next consider the capacity choices (i.e., investment and disinvestment options) of the firm. In each instant, the firm can spend the one-unit cost  $I$  to transform the growth option on the  $k^{th}$  output increment into the corresponding option to produce. Conversely, it can sell off the option to produce that same increment, cashing in the one-unit disinvestment proceeds  $S$ . For simplicity, we assume that, upon disinvesting an option to produce, the firm cannot reinstall it in the future, so disinvesting does not lead to reacquiring the corresponding growth option. Crucially, while the firm funds investments through raising equity, it instantaneously distributes the share  $q$  of disinvestment proceeds to its shareholders but keeps the residual in a savings account (earning the risk-free rate) to help it honor its debt obligations. The logic is that the firm's assets consist of easy-to-verify secured assets and hard-to-verify unsecured assets. While the firm must use the sales proceeds from secured assets to pay its debt, it can divert a share of the sales proceeds from unsecured assets to shareholders.

We finally discuss our capital structure assumptions. The firm is financed by common stock and a [Merton \(1974\)](#) zero-coupon bond. The bond obliges the firm to pay  $C$  at time  $T$ . Since the firm instantaneously pays profits to shareholders, it must pay its debt out of its remaining assets-in-place plus its saved disinvestment proceeds. If the firm cannot do so, it defaults, and debtholders receive the entire remaining firm value and saved disinvestment

proceeds.

### C. The Real Options Model Solution

We use standard contingent claims techniques to determine the values of the firm's assets-in-place and growth options (see [Dixit and Pindyck \(1994\)](#)). Specifically, our Internet Appendix shows that the value of the option to produce the  $k^{th}$  output increment,  $\Delta V(\theta; k)$ , is:

$$(7) \quad \Delta V(\theta; k) = \begin{cases} B_O \theta^{\beta_2} + \frac{\theta}{\delta} - \frac{c_1 + c_2 k + f}{r} & \text{if } \theta \geq c_1 + c_2 k, \\ A_I \theta^{\beta_1} + B_I \theta^{\beta_2} - \frac{f}{r} & \text{if } \theta^D \leq \theta < c_1 + c_2 k, \\ S & \text{if } \theta^D > \theta, \end{cases}$$

where  $r$  is the risk-free rate, and  $B_O$ ,  $A_I$ ,  $B_I$ ,  $\theta^D$ ,  $\beta_1$ , and  $\beta_2$  are free parameters defined in the Internet Appendix. Intuitively,  $B_O$  ( $A_I$ ) [ $B_I$ ] determines the value of the real option to switch off (switch on) [sell off] the option to produce, and  $\theta^D$  is the optimal disinvestment threshold (i.e., the price at or below which the firm optimally sells the option).<sup>22</sup>

Conversely, the value of the corresponding growth option,  $\Delta G(\theta; k)$ , is:

$$(8) \quad \Delta G(\theta; k) = \begin{cases} \Delta V(\theta; k) - I & \text{if } \theta \geq \theta^*, \\ G(\theta^*)^{\beta_1} & \text{if } \theta < \theta^*, \end{cases}$$

where  $G$  and  $\theta^*$  are new free parameters defined in the Internet Appendix. Intuitively,  $G$  determines the pre-exercise growth option value, and  $\theta^*$  is the optimal investment threshold

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<sup>22</sup>The closed-form solutions in this section assume that the firm optimally first switches off installed capacity before selling it. See our Internet Appendix for the case in which it optimally sells switched-on capacity.

(i.e., the price threshold at or above which the firm optimally exercises the option).

We can finally compute the total value of the firm,  $V(\theta)$ , from:

$$(9) \quad V(\theta) = \int_0^K \Delta V(\theta; k) dk + \int_K^\infty \Delta G(\theta; k) dk,$$

which we numerically approximate through the trapezoidal method.

Unfortunately, it is impossible to determine the values of the common stock and the zero-coupon bond in closed-form. As a result, we use a Monte Carlo simulation technique to obtain them. To do so, we write the value of the zero-coupon bond,  $D(\theta; T)$ , as:

$$(10) \quad D(\theta; T) = E^{\mathbb{Q}} \left[ e^{-rT} \min(C, V(\theta_T) + (1 - q)S_T) \right],$$

where  $E^{\mathbb{Q}}$  is the expectation operator under the equivalent martingale measure,  $V(\theta_T)$  the value of the firm's assets-in-place and growth options at time  $T$ , and  $S_T$  the compounded-up value of the disinvestment proceeds collected by the firm until that same time. We then simulate 100,000 sample paths for the daily output price  $\theta$  from time  $t = 0$  to  $T$  under the equivalent martingale measure, derive the firm's optimal capacity utilization, investment, and disinvestment choices at the end of each day, and calculate  $e^{-rT} \min(C, V(\theta_T) + (1 - q)S_T)$  for each path. Averaging over the 100,000  $e^{-rT} \min(C, V(\theta_T) + (1 - q)S_T)$  values, we obtain  $D(\theta; T)$ . Subtracting  $D(\theta; T)$  from  $V(\theta)$ , the initial firm value, we obtain the value of the common stock,  $E(\theta; T)$ . See our Internet Appendix for more technical details.

We follow [Cox and Rubinstein \(1985\)](#) in computing the instantaneous expected excess

return of the assets ( $X = V$ ), debt ( $X = D$ ), or stocks ( $X = E$ ),  $E[R_X^{ie}]$ , from:

$$\begin{aligned}
(11) \quad E[R_X^{ie}]dt &= E[dX/X] + \pi/X dt - r dt = E[dX/X] + \pi/X dt \\
&- (E^Q[dX/X] + \pi/X dt) \\
&= ((\mu - \delta)\theta X_\theta + \frac{1}{2}\sigma^2\theta^2 X_{\theta\theta} + X_t)/X dt \\
&- ((r - \delta)\theta X_\theta + \frac{1}{2}\sigma^2\theta^2 X_{\theta\theta} + X_t)/X dt \\
&= X_\theta(\theta/X)(\mu - r)dt,
\end{aligned}$$

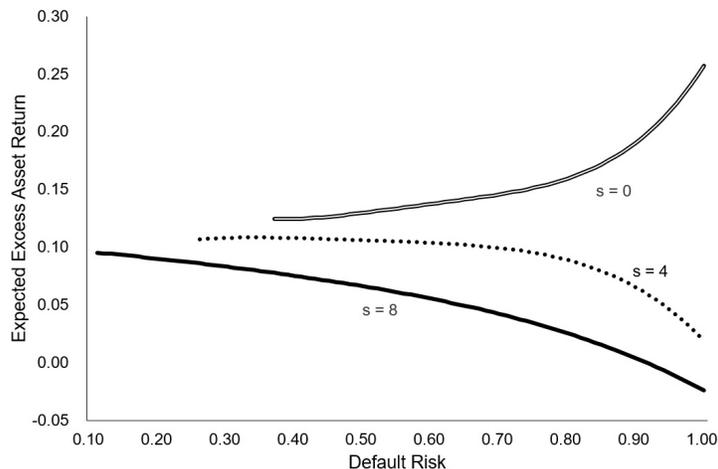
where  $\pi$  is the claim's payoff,  $X_\theta$  and  $X_t$  the first partial derivatives of the claim's value with respect to the output price  $\theta$  and time  $t$ , respectively, and  $X_{\theta\theta}$  the second partial derivative of that value with respect to the output price. We rely on Itô's lemma to derive the differential  $dX$ . Intuitively, equation (11) suggests that a claim's expected excess return is linear in its elasticity, defined as its delta,  $X_\theta$ , times the claim value-to-output price ratio,  $\theta/X$ .

#### D. The Effect of Real Disinvestments on the Distress Premium

We now investigate the real-options-model-implied effect of distress risk on the expected asset, stock, and debt return of the firm. In the base-case, we set the firm's initial capacity,  $K$ , to one. We further rely on an annualized total expected return,  $\mu$ , dividend yield,  $\delta$ , and volatility,  $\sigma$ , of the output-price mimicking portfolio of 12%, 8%, and 45%, respectively, and a risk-free rate,  $r$ , of 4%. We select the variable production cost parameters,  $c_1$  and  $c_2$ , to be 0.00 and 0.30, respectively, and the fixed production cost parameter,  $f$ , to be 0.70. We choose a bond repayment,  $C$ , and time-to-maturity,  $T$ , of 10.00 and 2.00,

### Figure 5: Disinvestments and the Default Risk-Expected Asset Return Relation

The figure plots the expected excess asset return against default risk separately for a disinvestment gain,  $S$ , of zero, four, and eight. See Section IV.D for more details about our basecase parameter value choices.

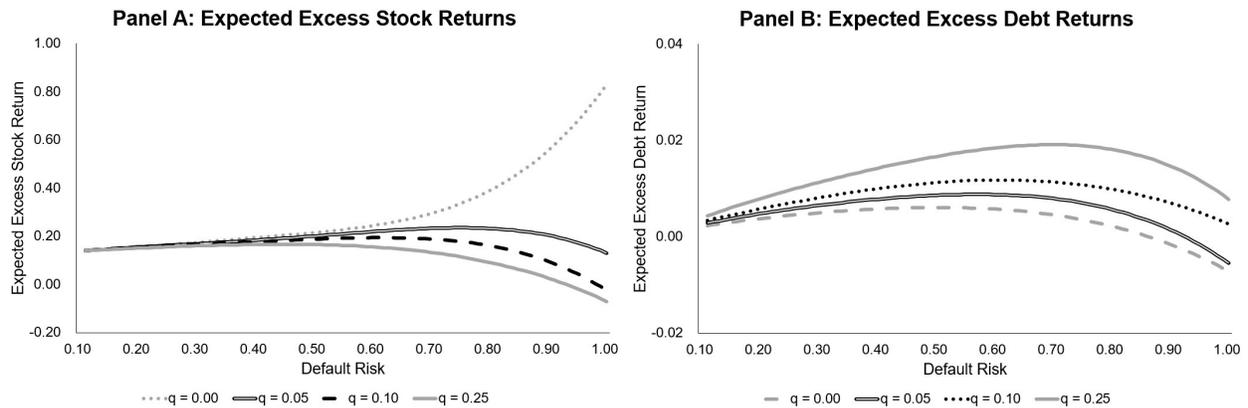


respectively. Consistent with distressed firms owning few valuable growth opportunities, we select an investment cost,  $I$ , of 100, ensuring that growth options make up an only small portion of total value.

We first study the effect of distress risk on the expected *asset* return separately for firms varying in the ease with which they can sell their assets-in-place. To do so, we always let the initial output price,  $\theta$ , range from the lowest value at which the firm does not immediately disinvest some capacity to 2.00. To vary the firm’s ability to disinvest, we set the disinvestment proceeds,  $S$ , to 0.00, 4.00, or 8.00. In Figure 5, we then plot the expected excess asset return (equation (11)) against distress risk (the probability that  $V(\theta_T) + (1 - q)S_T < C$ ) for each  $S$  value. The figure suggests that a greater ability to disinvest (i.e., a higher  $S$  value) lowers the expected asset returns especially for distressed firms. Specifically, while the expected asset returns of low-distress-risk firms are close to one another, those returns vividly rise (fall) with distress risk under a low (high) disinvestment ability. The reason is that distressed firms

## Figure 6: Disinvestments and the Default Risk-Expected Stock or Debt Return Relation

The figure plots the expected excess stock (Panel A) and debt (Panel B) return against default risk assuming a disinvestment gain,  $S$ , of eight and separately for a fraction of disinvestment proceeds distributed to shareholders,  $q$ , equal to zero, 0.05, 0.10, and 0.25. See Section IV.D for details about the basecase parameter values.



without valuable disinvestment options have high operating leverage boosting their systematic risk (see [Carlson, Fisher, and Giammarino \(2004\)](#) and [Cooper \(2006\)](#)). Yet, when distressed firms possess such options, the options' negative risk can dominate the positive operating leverage risk, lowering the firms' expected returns (see [Hackbarth and Johnson \(2015\)](#) and [Aretz and Pope \(2018\)](#)).

Notwithstanding, the more critical question for our purposes is whether a high disinvestment ability can also induce expected stock and/or debt returns to fall with distress risk. To tackle that question, Figure 6 plots the expected excess stock (Panel A) and debt (Panel B) return against distress risk under disinvestment proceeds,  $S$ , of 8.00 and a share of proceeds going to shareholders,  $q$ , of 0.00, 0.05, 0.10, and 0.25. The figure suggests that the model can yield a negative (or, more accurately, negatively hump-shaped) relation between distress risk and expected stock (debt) returns if a sufficient amount of disinvestment proceeds flow to stock (debt) claimants. In particular, the stock (debt) relation becomes negative if at least 5% (75%) of proceeds flow to stock (debt) claimants. Strikingly, the figure

also shows that the model can produce a jointly negative relation for stocks and debt if the lion share of proceeds flows to debtholders (e.g., 90%) but a small residual to shareholders (e.g., 10%).<sup>23</sup>

All in all, this section shows that, in a real options model of a stock-and-debt financed firm with capacity utilization, investment, and disinvestment choices, the ability to disinvest real assets can not only switch the distress risk-expected asset return relation from positive to negative but also the stock and debt relations — if a sufficient amount of disinvestment proceeds flows to the appropriate claimants. More importantly, such a model can yield jointly negative relations if the lion share but not all of the proceeds flows to debtholders.

## V. Empirical Tests of our Disinvestment Rationale

In this section, we empirically test the new implications of our real options model for the distress anomaly in Section IV. We first describe the variables used to proxy for the ease with which firms can disinvest their hard assets. We next offer the results from FM regressions of stock, bond, and loan returns on distress risk and controls separately estimated on firms with easier and harder-to-disinvest assets. We finally condition the regressions on volatility.

### A. The Disinvestment Ability Proxies

We use as proxies for the ease with which a firm can disinvest its hard assets: (i) Gu et al.’s (2018) asset inflexibility; (ii) Eisfeldt and Rampini’s (2006) asset reallocation; (iii)

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<sup>23</sup>Section IA.7.3. of our Internet Appendix offers comparative statics for our theoretical conclusions.

Schlingemann et al.'s (2002) asset liquidity; and (iv) Bai et al.'s (2024) investment skewness.<sup>24</sup> We calculate asset inflexibility as the range of the quarterly operating costs-to-quarterly sales ratio scaled by the volatility of the log change in the sales-to-assets ratio of a firm's industry, where operating costs are costs of goods sold plus selling, general, and administrative costs. Asset reallocation is a firm's annual acquisition expenses plus sales of property, plant, and equipment scaled by assets. Asset liquidity is the number of asset acquisition, firm acquisition, and merger deals in a firm's industry over the last year. Finally, investment skewness is the sample skewness of the annual growth in the sum of net property, plant, and equipment plus depreciation and amortization of a firm's industry. See Table A2 in Appendix A for more details.

The logic behind those proxies is as follows. A higher asset inflexibility signals a lower disinvestment ability since firms waiting longer to disinvest in response to negative shocks observe greater drops in their sales than operating costs (due to fixed operating costs). In turn, they have more variable operating costs-to-sales ratios. Conversely, a higher asset reallocation signals a greater disinvestment ability since higher-ability firms adjust their installed capacity more rapidly in response to shocks.<sup>25</sup> A higher asset liquidity signals a greater disinvestment ability since it indicates that firms' real assets are traded in more active and liquid secondary markets. Finally, a more positive investment skewness signals a lower disinvestment ability since the inability to disinvest truncates the investment

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<sup>24</sup>We also looked into Kim and Kung's (2017) asset redeployability, defined as the capital-expenditure-weighted average number of other industries in which the assets of the focal industry are employed. Since asset redeployability does, however, not condition the asset sales in our verification tests, we dropped it again.

<sup>25</sup>It may be surprising that the asset reallocation variable also considers a firm's capacity expansions to proxy for the ease with which the firm can sell off its real assets. The reason, however, is that firms with fewer disinvestment options are also more cautious in expanding their capacity.

distribution from the left.

In Table 7, we aim to validate the disinvestment ability proxies. To do so, we report the mean asset-sale-value-to-assets ratio for firms in the top (10), moderate (6-9), and low (1-5) distress deciles formed from the stock-bond sample in Section V.B separately for firms with an above third and below first quartile value for each disinvestment ability proxy. We obtain the asset-sale values from SDC Platinum. We compute the mean ratios by first averaging by portfolio formation date and then over our sample period. The table corroborates that firms classified by our proxies as high-disinvestment-ability markedly raise their asset sales in response to distress risk (see columns 1, 3, 5, and 7). For example, column 1 reveals that while low-distress and low-asset-inflexibility firms sell off about 7.41% of their assets, the corresponding number for high-distress firms is about 17.45%. In comparison, the asset sales of low-disinvestment-ability firms do not strongly relate to distress (see columns 2, 4, 6, and 8). Contrasting high-distress firms with a high and low disinvestment ability, the high-ability firms usually sell off more of their assets than their counterparts.

**Insert Table 7 Here.**

## **B. The Conditional Effect of Disinvestment Options**

We next test whether the ability of firms to disinvest real assets helps to explain the negative stock, bond, loan, and firm-asset distress premiums in Section III. To that end, Table 8 reports the results from repeating the stock and bond FM regressions in columns 1, 4, and 6 of Table 3 and the loan regressions in columns 6 and 8 of Table 6 on subsamples of firms with high (above third quartile) and low (below first) values for each disinvestment

ability proxy. Panels A, B, and C focus on stocks, bonds, and loans, respectively. As before, plain numbers are monthly premium estimates, while those in square brackets are Newey-West (1987)  $t$ -statistics with a twelve-month lag length. To conserve space, we report estimates and  $t$ -statistics only for the distress dummy variables but not the controls.

**Insert Table 8 Here.**

Starting off with our sample bonds and loans, Panels B and C suggest that their distress premiums are significantly more negative in the subsamples of firms with a higher disinvestment ability, in line with firms owning easy-to-disinvest hard assets selling those in distress and distributing most of the proceeds to debtholders. Columns 1 and 2 in Panel B, for example, show that while the monthly standard-return bond distress premium is an insignificant  $-0.09\%$  ( $t$ -statistic:  $-0.74$ ) in the high asset inflexibility (low disinvestment ability) subsample, the corresponding number is a significant  $-0.29\%$  ( $t$ -statistic:  $-3.24$ ) in the low inflexibility (high ability) subsample (contrast the coefficients on the *HighDistress* variable). As another example, columns 7 and 8 in Panel C reveal that while the standard-return loan distress premium is an insignificant  $-0.14\%$  ( $t$ -statistic:  $-0.94$ ) in the high investment skewness (low disinvestment ability) subsample, the corresponding number is a significant  $-0.69\%$  ( $t$ -statistic:  $-2.94$ ) in the low skewness (high ability) subsample. Overall, the bond premium is significantly negative at the 95% level in eight (out of eight) cases in the high but in only two in the low disinvestment-ability subsample. Conversely, the loan premium is significantly negative in six cases in the high but only in two in the low disinvestment-ability subsample.

Reverting to our sample stocks, Panel A shows that their distress premium tends to

be significantly more negative in the lower-disinvestment-ability subsamples. Columns 3 and 4, for example, suggest that while the monthly stock distress premium is an insignificant  $-0.15\%$  ( $t$ -statistic:  $-0.30$ ) in the high asset reallocation (high disinvestment ability) subsample, it is a significant  $-1.30\%$  ( $t$ -statistic:  $-2.70$ ) in the low reallocation (low ability) subsample. Overall, the stock distress premium is significantly negative at the 95% level in two (out of four) cases in the low but in none in the high disinvestment ability subsamples.

While it could be seen as puzzling that the ability to disinvest hard assets conditions the stock distress premium with the opposite sign compared to the bond and loan premiums, we note that easier-to-disinvest hard assets are likely attractive as collateral in debt contracts due to, for example, their high fire-sale values. As a result, it is likely that the proceeds from disinvesting them flow to debtholders, and not shareholders. In contrast, hard-to-disinvest hard assets are likely less attractive as collateral, allowing firms to channel some of the proceeds from disinvesting them to shareholders. Yet, as we demonstrate in Section IV, assigning an only small fraction of disinvestment proceeds to shareholders can already switch the distress risk-expected stock return relation from positive to negative.

### C. The Conditional Effect of Volatility

We now offer further evidence that the modulating effect of the disinvestment ability proxies on the stock, bond, and loan distress premiums in Section V.B can be attributed to variations in the ease with which firms are able to sell their hard assets. To that end, we recall that the value of real options (such as the disinvestment option) rises with uncertainty. The upshot is that the modulating effect of the disinvestment ability proxies should be

stronger for firms exposed to more uncertainty (see Grullon, Lyandres, and Zhdanov (2012) and our comparative statics on the effect of output-price volatility on the stock and debt distress premiums in Section IA.7.3. of our Internet Appendix). To test that conjecture, we choose those subsamples from Table 8 generating a stronger distress anomaly (i.e., the hard-to-disinvest stock and easy-to-disinvest bond and loan subsamples) and further split them according to the median of historical stock volatility. We estimate historical volatility from firm-specific regressions of the monthly stock return on the Fama-French (1993) three-factor model factors over the last two years of data and computing the annualized volatility of the residual. We finally repeat the relevant regressions from Table 8 separately on the subsamples with a high vs. low historical stock volatility.

Using a design similar to Table 8, Table 9 offers the subsample regression results. As always, plain numbers are monthly premium estimates, whereas those in square brackets are Newey-West (1987)  $t$ -statistics. The table supports the conjecture that the modulating effect of the disinvestment ability proxies is stronger in the higher-volatility subsamples. For example, while a high distress risk lowers the monthly mean stock return of high-volatility, low inflexible-asset firms by a significant 0.73% ( $t$ -statistic:  $-2.04$ ), the corresponding change is an insignificant  $-0.24\%$  ( $t$ -statistic:  $-0.54$ ) for low-volatility firms (contrast the *HighDistress* coefficient across columns 1 and 2 in Panel A). In the same vein, while a high distress risk lowers the monthly mean standard loan return of high-volatility, high asset-liquidity firms by a significant 0.55% ( $t$ -statistic:  $-2.29$ ), the corresponding change is an insignificant 0.00% ( $t$ -statistic: 0.03) for low volatility firms (contrast the same coefficient across columns 5 and 6 in Panel C.1). Overall, the modulating effect of the disinvestment

ability proxies is stronger in the high vs. the low volatility sample in all but two cases.

**Insert Table 9 Here.**

## VI. Concluding Remarks

We show that, analogous to the hump-shaped stock and negative bond mean return-distress relations exposed in the literature, those same relations are also negative for traded loans and firm assets, with the same firms appearing to be behind the non-positive relations. Spurred by the negative firm-asset relation, we speculate that the distress anomaly could be due to operational risk, such as the ability of firms to disinvest real assets in distress. We use a standard real options model of a stock-and-debt financed firm with capacity utilization, expansion, and contraction choices to back up our intuition. The model confirms that the ability to disinvest real assets can not only lower the expected asset returns of distressed firms but also their expected stock (debt) returns if a large enough amount of disinvestment proceeds flows to shareholders (debtholders). Critically, the model can produce jointly negative distress premiums if the lion share of disinvestment proceeds flows to debtholders but a small residual to shareholders. Using proxies for the ease with which a firm can disinvest its hard assets, we establish that while the bond and loan distress premiums become more negative with these proxies, the stock premium often becomes less negative with them, likely because easy-to-disinvest hard assets are more plausibly secured than their counterparts.

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**Table 1: Descriptive Statistics on Our Stock, Bond, and Loan Data**

The table offers descriptive statistics for our sample data, including the number of observations, the mean, the standard deviation (St. Dev.), and the first, 25th, 50th, 75th, and 99th percentiles, first calculated by sample month and then averaged over our sample period. Panels A and B focus on the stock-bond and the stock-bond-loan-asset sample, respectively. The stock variables in Panels A.1 and B.1 are the monthly stock return, stock market capitalization (“size”), the stock market beta, the book-to-market ratio, and the momentum return. The bond variables in Panels A.2 and B.2 are the monthly standard and [Bartram et al. \(BGN\) \(2025\)](#) bond return, the value-weighted average bond capitalization, the aggregate bond capitalization, years-to-maturity, the bond market beta, bond downside risk, bond reversal, and the most recent credit rating. The loan variables in Panel B.3 are the monthly standard and BGN loan return, the value-weighted average loan capitalization, the aggregate loan capitalization, and years-to-maturity. The firm-asset variables in Panel B.4 are the monthly standard and BGN firm-asset return and the aggregate firm-asset capitalization. The firm characteristics in Panels A.3 and B.5 are distress risk, asset growth, and profitability. All returns, downside risk, and bond reversal are in %, while all capitalizations are in billion \$. See [Table A1](#) in [Appendix A](#) for details about the analysis variables. While the sample period for the stock-bond sample is January 1986 to December 2020, the sample period for the stock-bond-loan-asset sample is August 1999 to April 2020.

	Obs	Mean	St. Dev.	Percentiles				
				1	25	50	75	99
	1	2	3	4	5	6	7	8
Panel A: Stock and Bond Sample								
Panel A.1: Stock Market Data								
Monthly Return (%)	3,480	1.01	12.27	-28.82	-5.24	0.47	6.50	37.50
Market Size (in Billion \$)	3,479	3.86	16.23	0.02	0.16	0.54	1.90	67.69
Stock Market Beta	2,797	0.96	0.70	-0.20	0.50	0.85	1.30	3.12
Book-to-Market	3,162	0.68	0.53	0.04	0.33	0.58	0.89	2.75
Momentum	3,235	0.09	0.37	-0.90	-0.11	0.09	0.28	1.13
Panel A.2: Bond Market Data (Firm-Level)								
Mth. Return - ME-to-ME (%)	764	0.71	2.32	-5.25	-0.03	0.67	1.42	6.93
Mth. Return - BGN (%)	779	0.72	2.33	-5.19	-0.02	0.67	1.42	6.96
Market Size (in Billion \$)	764	0.37	0.49	0.04	0.19	0.28	0.43	1.58
Total Mkt. Size (in Billion \$)	764	2.23	5.12	0.05	0.29	0.72	1.97	26.13
Maturity Time (in Years)	764	9.57	5.59	1.90	5.79	8.05	12.16	26.52
Bond Market Beta	606	0.58	0.44	-0.27	0.30	0.52	0.79	1.95
Downside Risk (%)	546	2.39	2.48	-0.01	1.03	1.83	2.95	12.55
Bond Reversal (%)	758	0.78	2.23	-4.68	-0.01	0.68	1.44	7.27
Credit Rating	700	8.76	3.64	2.05	6.13	8.17	11.19	16.99
Panel A.3: Firm Fundamental Data								
Distress Risk (%)	3,480	0.08	0.16	0.00	0.02	0.04	0.08	0.70
Asset Growth	3,252	0.16	0.33	-0.45	0.01	0.08	0.21	1.67
Profitability	3,365	0.30	0.28	-0.33	0.09	0.27	0.46	1.21

(continued on next page)

Panel B: Stock, Bond, and Loan Sample								
Panel B.1: Stock Market Data								
Monthly Return (%)	179	0.77	14.28	-34.78	-6.25	0.24	7.09	45.81
Market Size (in Billion \$)	179	6.38	22.57	0.04	0.57	1.45	3.61	134.16
Stock Market Beta	141	1.20	0.82	-0.10	0.65	1.07	1.59	4.06
Book-to-Market	132	0.74	0.71	0.04	0.30	0.54	0.92	3.69
Momentum	148	-0.02	0.47	-1.38	-0.26	0.04	0.27	1.00
Panel B.2: Bond Market Data (Firm-Level)								
Mth. Return - ME-to-ME (%)	103	0.65	4.24	-13.96	-0.38	0.63	1.78	14.38
Mth. Return - BGN (%)	108	0.68	4.31	-13.49	-0.38	0.64	1.78	14.22
Market Size (in Billion \$)	103	0.53	0.46	0.05	0.26	0.39	0.61	2.41
Total Mkt. Size (in Billion \$)	103	3.28	10.29	0.06	0.35	0.78	1.81	66.38
Maturity Time (in Years)	103	6.81	3.48	1.86	5.00	6.22	7.62	21.77
Bond Market Beta	76	0.45	0.52	-0.50	0.14	0.33	0.61	2.51
Downside Risk (%)	65	3.56	4.14	-0.30	1.14	2.31	4.35	22.20
Bond Reversal (%)	102	0.66	4.04	-12.87	-0.37	0.62	1.76	14.05
Credit Rating	100	13.37	3.43	3.33	11.70	14.17	15.67	19.26
Panel B.3: Loan Market Data (Firm-Level)								
Mth. Return - ME-to-ME (%)	179	0.30	2.13	-6.57	-0.04	0.32	0.75	6.16
Mth. Return - BGN (%)	186	0.34	2.05	-6.24	0.02	0.36	0.75	6.06
Market Size (in Billion \$)	179	0.46	0.48	0.03	0.17	0.30	0.58	2.26
Total Mkt. Size (in Billion \$)	179	0.80	1.07	0.04	0.24	0.45	0.94	5.67
Maturity Time (in Years)	179	4.09	1.42	0.82	3.11	4.17	5.13	6.82
Panel B.4: Firm Asset Data								
Mth. Return - ME-to-ME (%)	179	0.54	7.23	-19.61	-2.94	0.44	3.92	21.58
Mth. Return - BGN (%)	186	0.55	6.95	-18.78	-2.77	0.43	3.73	21.07
Market Size (in Billion \$)	179	10.51	35.60	0.22	1.23	2.89	6.64	226.06
Panel B.5: Firm Fundamental Data								
Distress Risk (%)	179	0.21	0.53	0.01	0.03	0.06	0.15	2.69
Asset Growth	173	0.13	0.31	-0.48	-0.03	0.05	0.19	1.35
Profitability	174	0.28	0.21	-0.03	0.14	0.23	0.35	1.10

**Table 2: Stock and Bond Portfolios Sorted on Distress Risk**

The table offers the mean returns and alphas of stock and bond portfolios univariately sorted on distress risk in the stock-bond sample. Panels A and B focus on stocks and bonds, whereas subpanels B.1 and B.2 concentrate on standard and [Bartram et al. \(BGN\) \(2025\)](#) bond returns, all respectively. We sort our sample stocks or firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm) into portfolios according to the decile breakpoints of [Campbell et al. \(2008\)](#) distress risk at the end of month  $t - 1$ . We value (columns 2 to 5) or equally (6 to 9) weight the portfolios and hold them over month  $t$ , where we use a firm’s total stock or bond capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the fifth (top) [top] decile portfolio and short the bottom (fifth) [bottom] (“Middle–Low” (“High–Middle”) [“High–Low”]). The table reports the mean distress risk (column 1), the mean monthly excess returns (2 and 6), and various factor-model alphas (3, 4, 5, 7, 8, and 9) of the portfolios. FF3S, FF5S, and FF6S indicate the [Fama and French \(1993\)](#) three-factor, the [Fama and French \(2015\)](#) five-factor, and the [Fama and French \(2016\)](#) six-factor model, respectively. FF5SB, SB8, and SB14 indicate the [Fama and French \(1993\)](#) five-factor stock-bond, the eight-factor stock-bond, and the 14-factor stock-bond model, respectively. Plain numbers are monthly estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics with a twelve-month lag length. The sample period is January 1986 to December 2020.

Decile	Value-Weighted Portfolios					Equally-Weighted Portfolios			
	Mean	Mean				Mean			
	Distress Risk	Monthly Return	Monthly Alpha	Monthly Alpha	Monthly Alpha	Monthly Return	Monthly Alpha	Monthly Alpha	Monthly Alpha
	1	2	3	4	5	6	7	8	9
Panel A: Stock Returns (Mean Monthly # Per Porfolio: 348)									
1 (Low)	0.01	0.66	−0.01	−0.01	−0.03	0.71	0.04	0.00	0.00
2	0.01	0.67	0.02	0.03	−0.02	0.69	−0.01	−0.02	−0.04
3	0.02	0.64	0.00	−0.06	−0.09	0.83	0.14	0.09	0.07
4	0.03	0.77	0.09	0.02	0.01	0.84	0.12	0.02	0.02
5 (Middle)	0.03	0.84	0.10	0.10	0.10	0.87	0.13	0.04	0.06
6	0.05	0.78	−0.03	−0.04	0.00	0.87	0.10	0.03	0.07
7	0.06	0.82	−0.09	0.04	0.10	0.83	0.01	0.03	0.09
8	0.08	0.86	−0.14	0.10	0.17	0.84	−0.07	0.02	0.11
9	0.13	0.32	−0.87	−0.49	−0.36	0.52	−0.52	−0.30	−0.17
10 (High)	0.32	−0.20	−1.60	−1.22	−1.01	−0.17	−1.36	−1.04	−0.85
Middle–Low		0.18	0.11	0.11	0.14	0.17	0.10	0.04	0.07
		[1.10]	[0.71]	[0.67]	[0.89]	[1.16]	[0.80]	[0.34]	[0.62]
High–Middle		−1.03	−1.70	−1.33	−1.12	−1.05	−1.49	−1.08	−0.91
		[−2.30]	[−4.26]	[−3.64]	[−2.89]	[−3.65]	[−6.12]	[−5.62]	[−4.93]
High–Low		−0.85	−1.59	−1.22	−0.98	−0.88	−1.40	−1.04	−0.84
		[−1.76]	[−3.65]	[−2.82]	[−2.25]	[−3.08]	[−5.62]	[−4.15]	[−3.73]
Alpha			FF3S	FF5S	FF6S		FF3S	FF5S	FF6S

(continued on next page)

Panel B: Firm-Level Bond Returns

Panel B.1: Month-End to Month-End Bond Returns (Mean Monthly # Per Porfolio: 76)									
1 (Low)	0.01	0.51	0.30	0.25	0.26	0.55	0.35	0.30	0.31
2	0.02	0.44	0.21	0.16	0.18	0.52	0.30	0.25	0.29
3	0.02	0.47	0.24	0.19	0.21	0.50	0.29	0.23	0.25
4	0.03	0.47	0.26	0.19	0.22	0.51	0.30	0.23	0.28
5 (Middle)	0.04	0.45	0.22	0.16	0.20	0.47	0.26	0.19	0.24
6	0.05	0.43	0.20	0.14	0.18	0.46	0.24	0.17	0.23
7	0.06	0.21	-0.01	-0.03	0.01	0.47	0.25	0.18	0.21
8	0.07	0.38	0.15	0.07	0.10	0.43	0.21	0.13	0.19
9	0.11	0.39	0.14	0.03	0.09	0.44	0.21	0.11	0.18
10 (High)	0.33	0.16	-0.15	-0.32	-0.20	0.24	-0.04	-0.22	-0.10
Middle-Low		-0.06	-0.08	-0.09	-0.06	-0.08	-0.10	-0.11	-0.07
		[-3.08]	[-4.20]	[-4.93]	[-2.06]	[-3.81]	[-5.18]	[-6.27]	[-2.94]
High-Middle		-0.29	-0.37	-0.48	-0.41	-0.23	-0.30	-0.41	-0.34
		[-3.10]	[-4.84]	[-6.00]	[-6.16]	[-2.43]	[-4.18]	[-5.62]	[-6.32]
High-Low		-0.35	-0.45	-0.58	-0.47	-0.30	-0.40	-0.51	-0.41
		[-3.53]	[-5.76]	[-7.27]	[-7.51]	[-3.04]	[-5.28]	[-6.88]	[-7.27]
Panel B.2: <a href="#">Bartram et al. (2025)</a> Bond Returns (Mean Monthly # Per Porfolio: 78)									
Middle-Low		-0.07	-0.08	-0.10	-0.06	-0.07	-0.09	-0.10	-0.07
		[-3.27]	[-4.25]	[-5.18]	[-2.22]	[-4.07]	[-5.05]	[-6.54]	[-3.13]
High-Middle		-0.28	-0.37	-0.48	-0.40	-0.22	-0.29	-0.40	-0.34
		[-3.11]	[-4.85]	[-6.02]	[-6.20]	[-2.35]	[-4.11]	[-5.66]	[-6.34]
High-Low		-0.35	-0.45	-0.57	-0.47	-0.29	-0.38	-0.50	-0.41
		[-3.56]	[-5.79]	[-7.34]	[-7.59]	[-2.96]	[-5.24]	[-6.95]	[-7.23]
Alpha			FF5SB	SB8	SB14		FF5SB	SB8	SB14

**Table 3: Stock and Bond Regressions on Distress Risk**

The table offers the results from Fama and MacBeth (1973) regressions of the excess returns of single stocks, single stocks with bonds, and all, investment-grade (IG), and speculative-grade (SG) firm-specific bond portfolios over month  $t$  on two distress dummy variables, interactions, and controls at the end of month  $t - 1$  in the stock-bond sample. We create the bond portfolios by forming value-weighted portfolios of all outstanding bonds by firm. Investment (speculative) grade bonds have a rating equal to or above (below) BBB- at the end of month  $t - 1$ . The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if Campbell et al. (2008) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. *LowS/BRet* is a dummy equal to one if the return of the other asset class is below the first cross-sectional quartile and else zero. See Table A1 in Appendix A for details about the controls. Plain numbers are monthly premium estimates (in %), while those in square parentheses are Newey and West (1987)  $t$ -statistics calculated with a twelve-month lag length. The columns labelled “ME-ME” (“BGN”) rely on standard (Bartram et al. (BGN) (2025)) returns. The sample period is January 1986 to December 2020.

	All Stocks	Stocks with Bonds	Stocks with Bonds	All Bonds	All Bonds	All Bonds	IG Bonds	SG Bonds
	1	2	3	4	5	6	7	8
<i>HighDistress</i> ( <i>HD</i> )	-0.61 [-2.82]	-0.48 [-2.55]	1.24 [4.81]	-0.25 [-4.61]	0.09 [2.25]	-0.24 [-4.61]	-0.12 [-3.76]	-0.39 [-4.29]
<i>LowDistress</i> ( <i>LD</i> )	-0.24 [-2.61]	-0.21 [-2.08]	-0.55 [-5.02]	0.06 [4.10]	0.02 [1.80]	0.05 [3.88]	0.04 [3.94]	0.11 [2.26]
<i>HD</i> × <i>LowS/BRet</i>			-4.37 [-8.42]		-0.96 [-5.92]			
<i>LD</i> × <i>LowS/BRet</i>			1.26 [8.84]		0.18 [4.73]			
<i>MarketBeta</i>	0.07 [0.51]	0.02 [0.18]	0.03 [0.24]	0.05 [2.41]	0.08 [3.77]	0.05 [2.37]	0.02 [0.99]	0.06 [1.17]
<i>MarketSize</i>	0.02 [0.59]	0.00 [-0.13]	-0.05 [-1.37]	-0.03 [-3.16]	-0.04 [-3.54]	-0.03 [-3.28]	-0.01 [-1.62]	-0.06 [-2.45]
<i>BookToMarket</i>	0.11 [1.43]	0.05 [0.61]	0.08 [1.32]	0.00 [-0.27]	0.00 [-0.22]	0.00 [-0.24]	-0.01 [-1.11]	-0.01 [-0.24]
<i>Momentum</i>	0.86 [4.13]	0.79 [2.99]	0.74 [2.46]	0.08 [1.69]	0.04 [1.06]	0.08 [1.65]	0.13 [3.60]	-0.13 [-1.13]
<i>AssetGrowth</i>	-0.38 [-3.26]	-0.49 [-3.43]	-0.42 [-3.10]	0.04 [1.00]	0.05 [1.58]	0.04 [1.20]	0.03 [0.95]	-0.14 [-1.67]
<i>Profitability</i>	0.63 [3.96]	0.54 [2.24]	0.69 [2.74]	0.01 [0.23]	0.03 [0.57]	0.00 [0.02]	-0.03 [-1.01]	-0.03 [-0.21]
<i>BondMarketBeta</i>				0.11 [1.08]	0.09 [0.91]	0.09 [0.91]	-0.09 [-0.74]	0.26 [1.60]
<i>BondSize</i>				-0.03 [-1.62]	-0.02 [-1.24]	-0.04 [-2.31]	-0.03 [-2.00]	-0.02 [-0.42]
<i>BondMaturity</i>				0.08 [2.41]	0.08 [2.50]	0.08 [2.43]	0.08 [2.46]	0.09 [1.52]
<i>BondCreditRating</i>				0.11 [2.67]	0.12 [3.21]	0.10 [2.53]	0.07 [2.31]	0.23 [1.08]
<i>BondDownsideRisk</i>				3.74 [4.37]	4.00 [4.77]	3.71 [4.33]	2.62 [3.40]	1.78 [1.19]
<i>BondReversal</i>				-9.71 [-5.46]	-10.06 [-5.69]	-9.71 [-5.54]	-8.96 [-5.52]	-7.84 [-4.01]
Return Type	ME-ME	ME-ME	ME-ME	ME-ME	ME-ME	BGN	ME-ME	ME-ME
Static Effects	No	No	Yes	No	Yes	No	No	No

**Table 4: Stock, Bond, and Loan Portfolios Sorted on Distress Risk**

The table offers the mean returns and alphas of stock, bond, and loan portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample. Panels A, B, and C focus on stocks, bonds, and loans, whereas the first and second subpanels in Panels B and C concentrate on standard and Bartram et al. (BGN) (2025) returns, all respectively. We sort our sample stocks, firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm), and firm-specific loan portfolios (i.e., the value-weighted portfolios of all outstanding traded loans by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month  $t - 1$ . We value (columns 2 to 5) or equally (6 to 9) weight the portfolios and hold them over month  $t$ , where we use a firm’s total stock, bond, or loan capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] (“Middle–Low” (“High–Middle”) [“High–Low”]). The table reports the mean distress risk (column 1), the mean monthly excess returns (2 and 6), and various factor-model alphas (3, 4, 5, 7, 8, and 9) of the portfolios. FF3S, FF5S, and FF6S indicate the Fama and French (1993) three-factor, the Fama and French (2015) five-factor, and the Fama and French (2016) six-factor model, respectively. FF5SB, SB8, and SB14 indicate the Fama and French (1993) five-factor stock-bond, the eight-factor stock-bond, and the 14-factor stock-bond model, respectively. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987)  $t$ -statistics with a twelve-month lag length. The sample period is August 1999 to April 2020.

Quintile	Value-Weighted Portfolios					Equally-Weighted Portfolios			
	Mean	Mean				Mean			
	Distress Risk	Monthly Return	Monthly Alpha	Monthly Alpha	Monthly Alpha	Monthly Return	Monthly Alpha	Monthly Alpha	Monthly Alpha
	1	2	3	4	5	6	7	8	9
Panel A: Stock Returns (Mean Monthly # Per Porfolio: 36)									
1 (Low)	0.02	0.45	-0.01	-0.09	-0.09	0.43	-0.05	-0.15	-0.15
2	0.03	0.29	-0.23	-0.35	-0.35	0.45	-0.10	-0.31	-0.30
3 (Middle)	0.06	1.12	0.48	0.33	0.37	1.11	0.44	0.21	0.27
4	0.13	0.28	-0.52	-0.51	-0.48	0.60	-0.18	-0.26	-0.20
5 (High)	0.67	-0.51	-1.56	-1.34	-1.21	-0.28	-1.32	-1.06	-0.94
Middle–Low		0.67	0.49	0.42	0.46	0.68	0.49	0.36	0.42
		[1.93]	[1.68]	[1.40]	[1.53]	[2.17]	[1.78]	[1.32]	[1.58]
High–Middle		-1.63	-2.03	-1.67	-1.58	-1.39	-1.76	-1.27	-1.21
		[-2.45]	[-3.78]	[-3.58]	[-3.10]	[-2.59]	[-4.10]	[-3.77]	[-3.33]
High–Low		-0.96	-1.54	-1.25	-1.12	-0.71	-1.27	-0.91	-0.79
		[-1.52]	[-3.67]	[-3.16]	[-2.49]	[-1.29]	[-3.46]	[-2.69]	[-2.20]
Alpha			FF3S	FF5S	FF6S		FF3S	FF5S	FF6S

(continued on next page)

Panel B: Firm-Level Bond Returns									
Panel B.1: Month-End to Month-End Bond Returns (Mean Monthly # Per Portfolio: 21)									
1 (Low)	0.02	0.62	0.42	0.30	0.19	0.64	0.47	0.36	0.31
2	0.04	0.62	0.44	0.30	0.29	0.62	0.45	0.29	0.32
3 (Middle)	0.06	0.69	0.47	0.30	0.20	0.63	0.45	0.27	0.22
4	0.13	0.55	0.30	0.13	0.18	0.60	0.40	0.21	0.25
5 (High)	0.67	-0.04	-0.45	-0.85	-0.68	0.06	-0.35	-0.71	-0.48
Middle-Low		0.07	0.06	0.00	0.01	-0.01	-0.02	-0.08	-0.09
		[1.16]	[0.97]	[0.00]	[0.22]	[-0.18]	[-0.43]	[-1.45]	[-1.36]
High-Middle		-0.73	-0.92	-1.15	-0.88	-0.58	-0.79	-0.99	-0.70
		[-2.52]	[-3.58]	[-4.53]	[-3.58]	[-2.07]	[-3.32]	[-4.01]	[-3.08]
High-Low		-0.66	-0.86	-1.15	-0.87	-0.58	-0.82	-1.07	-0.79
		[-2.11]	[-3.26]	[-4.50]	[-3.52]	[-1.96]	[-3.31]	[-4.44]	[-3.61]
Panel B.2: <a href="#">Bartram et al. (2025)</a> Bond Returns (Mean Monthly # Per Portfolio: 22)									
Middle-Low		0.03	0.00	-0.07	-0.04	-0.03	-0.06	-0.13	-0.12
		[0.36]	[0.04]	[-1.25]	[-0.64]	[-0.36]	[-0.81]	[-1.74]	[-1.63]
High-Middle		-0.72	-0.89	-1.11	-0.92	-0.59	-0.77	-0.96	-0.73
		[-2.62]	[-3.56]	[-4.53]	[-3.86]	[-2.21]	[-3.33]	[-4.16]	[-3.47]
High-Low		-0.69	-0.89	-1.18	-0.95	-0.61	-0.82	-1.09	-0.85
		[-2.27]	[-3.33]	[-4.57]	[-3.73]	[-2.10]	[-3.36]	[-4.62]	[-3.78]
Alpha			FF5SB	SB8	SB14		FF5SB	SB8	SB14
Panel C: Firm-Level Loan Returns									
Panel C.1: Month-End to Month-End Loan Returns (Mean Monthly # Per Portfolio: 36)									
1 (Low)	0.02	0.27	0.24	0.14	0.12	0.28	0.25	0.15	0.17
2	0.03	0.25	0.22	0.11	0.10	0.26	0.22	0.12	0.11
3 (Middle)	0.06	0.22	0.18	0.06	0.06	0.24	0.21	0.09	0.12
4	0.13	0.15	0.11	-0.05	-0.02	0.17	0.13	-0.01	0.05
5 (High)	0.67	-0.18	-0.27	-0.46	-0.24	-0.16	-0.22	-0.38	-0.18
Middle-Low		-0.06	-0.06	-0.08	-0.06	-0.04	-0.04	-0.06	-0.05
		[-1.58]	[-2.04]	[-2.30]	[-1.88]	[-0.94]	[-0.94]	[-1.40]	[-1.47]
High-Middle		-0.39	-0.45	-0.53	-0.30	-0.41	-0.43	-0.47	-0.30
		[-2.38]	[-3.08]	[-4.30]	[-2.66]	[-2.55]	[-3.04]	[-3.94]	[-2.77]
High-Low		-0.45	-0.51	-0.61	-0.36	-0.44	-0.46	-0.53	-0.35
		[-2.38]	[-3.35]	[-4.82]	[-2.89]	[-2.48]	[-3.23]	[-4.34]	[-2.99]
Panel C.2: <a href="#">Bartram et al. (2025)</a> Loan Returns (Mean Monthly # Per Portfolio: 37)									
Middle-Low		-0.04	-0.03	-0.06	-0.04	-0.01	-0.01	-0.03	0.00
		[-1.18]	[-1.14]	[-2.09]	[-1.17]	[-0.34]	[-0.15]	[-0.83]	[0.04]
High-Middle		-0.31	-0.36	-0.43	-0.28	-0.35	-0.38	-0.42	-0.29
		[-2.57]	[-3.46]	[-4.50]	[-3.15]	[-2.75]	[-3.27]	[-4.13]	[-3.30]
High-Low		-0.34	-0.40	-0.49	-0.32	-0.36	-0.38	-0.45	-0.29
		[-2.47]	[-3.43]	[-4.81]	[-3.21]	[-2.45]	[-3.17]	[-4.33]	[-2.98]
Alpha			FF5S	SB8	SB14		FF5S	SB8	SB14

**Table 5: Firm-Asset Portfolios Sorted on Distress Risk**

The table offers the mean returns and alphas of firm-asset portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample. Panels A and B focus on standard and Bartram et al. (BGN) (2025) returns, all respectively. We sort our sample firm-assets (i.e., the value-weighted portfolios of all stock, value-weighted bond, and value-weighted traded loan portfolios by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month  $t - 1$ . We value (columns 2 to 5) or equally (6 to 9) weight the portfolios and hold them over month  $t$ , where we use a firm’s total firm-asset capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] (“Middle–Low” (“High–Middle”) [“High–Low”]). The table reports the mean distress risk (column 1), the mean monthly excess returns (2 and 6), and various factor-model alphas (3, 4, 5, 7, 8, and 9) of the portfolios. SB8, SB14, and SB17 indicate the eight-factor stock-bond, 14-factor stock-bond, and 17-factor stock-bond model, respectively. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987)  $t$ -statistics with a twelve-month lag length. The sample period is August 1999 to April 2020.

Quintile	Value-Weighted Portfolios					Equally-Weighted Portfolios			
	Mean	Mean				Mean			
	Distress Risk	Monthly Return	Monthly Alpha	Monthly Alpha	Monthly Alpha	Monthly Return	Monthly Alpha	Monthly Alpha	Monthly Alpha
	1	2	3	4	5	6	7	8	9
Panel A: Month-End to Month-End Firm-Asset Returns (Mean Monthly # Per Porfolio: 36)									
1 (Low)	0.02	0.43	0.02	-0.06	-0.03	0.40	-0.02	-0.08	-0.08
2	0.03	0.32	-0.13	-0.22	-0.21	0.43	-0.07	-0.16	-0.13
3 (Middle)	0.06	0.75	0.27	0.13	0.09	0.75	0.25	0.11	0.11
4	0.13	0.31	-0.14	-0.25	-0.24	0.44	0.00	-0.10	-0.11
5 (High)	0.67	-0.28	-0.63	-0.99	-0.82	-0.22	-0.54	-0.84	-0.66
Middle–Low		0.32	0.26	0.19	0.11	0.35	0.27	0.19	0.20
		[1.50]	[1.29]	[0.93]	[0.50]	[1.85]	[1.70]	[1.14]	[1.13]
High–Middle		-1.02	-0.90	-1.12	-0.91	-0.97	-0.79	-0.95	-0.77
		[-3.07]	[-3.01]	[-3.38]	[-3.59]	[-4.00]	[-3.93]	[-4.54]	[-4.60]
High–Low		-0.70	-0.64	-0.93	-0.80	-0.62	-0.52	-0.76	-0.58
		[-2.39]	[-2.55]	[-3.15]	[-2.64]	[-2.69]	[-3.13]	[-4.47]	[-3.02]
Panel B: Bartram et al. (2025) Firm-Asset Returns (Mean Monthly # Per Porfolio: 37)									
Middle–Low		0.24	0.26	0.21	0.21	0.34	0.33	0.24	0.28
		[1.25]	[1.28]	[1.03]	[0.95]	[2.15]	[2.21]	[1.56]	[1.75]
High–Middle		-0.90	-0.78	-1.01	-0.80	-0.84	-0.69	-0.82	-0.64
		[-3.24]	[-2.93]	[-3.34]	[-3.18]	[-4.12]	[-3.96]	[-4.28]	[-4.05]
High–Low		-0.66	-0.52	-0.80	-0.59	-0.50	-0.36	-0.58	-0.36
		[-2.91]	[-2.63]	[-3.25]	[-2.20]	[-2.76]	[-2.75]	[-4.09]	[-2.21]
Alpha			SB8	SB11	SB17		FF8	SB11	SB17

**Table 6: Stock, Bond, Loan, and Firm-Asset Regressions on Distress Risk**

The table offers the results from [Fama and MacBeth \(1973\)](#) regressions of the excess returns of single stocks, firm-specific bond portfolios, firm-specific loan portfolios, and firm asset portfolios over month  $t$  on two distress risk dummy variables, interactions, and several control variables measured at the end of month  $t - 1$  in the stock-bond-loan-asset sample. We create the firm-specific bond (loan) [asset] portfolios through forming value-weighted portfolios of all bonds (loans) [assets] outstanding by firm at the end of that month. We only include a firm in the regressions if we have non-missing stock and loan (but not necessarily bond) data for the firm at the end of month  $t - 1$ . The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if [Campbell et al. \(2008\)](#) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. *LowSRet* (*LowBRet*) [*LowLRet*] is a dummy equal to one if the return of the corresponding stock (bond) [loan] is within the first tercile and else zero. See [Table A1](#) in [Appendix A](#) for more details about the control variables. Plain numbers are monthly premium estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics calculated with a twelve-month lag length. The columns labelled “ME-ME” (“BGN”) rely on standard ([Bartram et al. \(BGN\) \(2025\)](#)) returns. The sample period is August 1999 to April 2020.

	Stocks with Loans	Stocks with Loans	Bonds w/ Stocks & Loans	Bonds w/ Stocks & Loans	Bonds w/ Stocks & Loans	Loans with Stocks	Loans with Stocks	Loans with Stocks	Assets w/ Stocks & Loans	Assets w/ Stocks & Loans
	1	2	3	4	5	6	7	8	9	10
<i>HighDistress (HD)</i>	-1.06 [-2.23]	-0.11 [-0.16]	-0.72 [-2.55]	-0.16 [-0.28]	-0.78 [-2.99]	-0.46 [-2.44]	-0.27 [-1.95]	-0.29 [-2.49]	-0.79 [-3.21]	-0.75 [-3.09]
<i>LowDistress (LD)</i>	-0.11 [-0.37]	-0.78 [-2.23]	0.19 [2.07]	-0.20 [-1.30]	0.10 [0.70]	0.00 [0.02]	-0.08 [-1.31]	0.01 [0.28]	0.02 [0.12]	0.00 [-0.00]
<i>HD × LowLRet</i>		-1.28 [-0.93]		-0.35 [-0.47]						
<i>LD × LowLRet</i>		2.31 [4.50]		0.32 [1.22]						
<i>HD × LowSRet</i>				-1.82 [-3.15]			-0.34 [-1.79]			
<i>LD × LowSRet</i>				1.18 [3.67]			0.29 [3.43]			
<i>MarketBeta</i>	0.03 [0.11]	0.03 [0.10]	-0.02 [-0.24]	0.03 [0.35]	-0.05 [-0.46]	0.02 [0.27]	0.03 [0.55]	0.03 [0.65]	0.01 [0.05]	-0.08 [-0.52]

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<i>MarketSize</i>	-0.11 [-1.48]	-0.09 [-1.24]	-0.08 [-1.56]	-0.12 [-1.82]	-0.18 [-2.17]	0.01 [0.53]	0.00 [-0.06]	0.00 [0.08]	-0.06 [-1.54]	-0.07 [-1.66]
<i>BookToMarket</i>	-0.03 [-0.17]	0.03 [0.18]	0.05 [0.88]	0.06 [1.19]	0.04 [0.83]	0.01 [0.28]	0.01 [0.26]	-0.02 [-0.89]	-0.03 [-0.37]	-0.13 [-1.40]
<i>Momentum</i>	0.30 [0.56]	0.09 [0.16]	0.13 [0.63]	-0.13 [-0.68]	0.27 [1.28]	0.23 [2.47]	0.19 [2.17]	0.20 [2.69]	0.23 [0.96]	0.39 [1.69]
<i>AssetGrowth</i>	-0.12 [-0.35]	-0.13 [-0.35]	0.06 [0.42]	0.05 [0.43]	-0.10 [-0.72]	-0.06 [-0.80]	-0.07 [-0.92]	-0.04 [-0.85]	-0.02 [-0.15]	-0.02 [-0.16]
<i>Profitability</i>	0.97 [1.03]	0.89 [0.89]	-0.12 [-0.47]	0.05 [0.20]	-0.08 [-0.34]	0.20 [1.62]	0.14 [1.15]	0.22 [1.93]	0.07 [0.17]	0.32 [0.69]
<i>BondMarketBeta</i>			0.85 [0.97]	0.90 [1.04]	0.95 [1.12]					
<i>BondSize</i>			-0.01 [-0.21]	0.03 [0.56]	0.04 [0.69]					
<i>BondMaturity</i>			0.19 [1.84]	0.19 [1.89]	0.14 [1.18]					
<i>BondCreditRating</i>			0.36 [2.17]	0.37 [1.71]	0.25 [1.17]					
<i>BondDownsideRisk</i>			-3.37 [-0.94]	1.46 [0.44]	-1.12 [-0.31]					
<i>BondReversal</i>			-9.58 [-3.08]	-10.06 [-3.16]	-10.91 [-3.54]					
<i>LoanSize</i>			-0.03 [-0.66]	-0.01 [-0.26]	-0.03 [-0.70]	-0.03 [-1.75]	-0.03 [-1.44]	-0.01 [-0.30]	-0.09 [-1.50]	-0.05 [-0.85]
<i>LoanMaturity</i>			0.04 [0.38]	0.10 [1.05]	-0.19 [-0.94]	-0.05 [-0.87]	-0.05 [-0.79]	-0.01 [-0.28]	-0.06 [-0.60]	-0.15 [-1.53]
Return Type	ME-ME	ME-ME	ME-ME	ME-ME	BGN	ME-ME	ME-ME	BGN	ME-ME	BGN
Static Effects	No	Yes	No	Yes	No	No	Yes	No	No	No

**Table 7: The Asset Sales of Distressed Firms**

The table offers the mean asset sales of firms with easy vs. difficult to disinvest hard assets conditional on a low, moderate, or high distress risk in the stock-bond sample. We measure asset sales as the ratio of asset-sale deal values over the current calendar month  $t$  to total assets from the fiscal year ending in calendar year  $t - 1$ , replacing missing deal values with the prediction from a regression of available values on the change in a firm's property, plant, and equipment. We classify firms with a [Campbell et al. \(2008\)](#) distress risk at the end of calendar year  $t - 1$  below the median (between the median and the ninth decile) [above the ninth decile] as low (moderate) [high] distress risk firms. Conversely, we classify firms with an *AssetInflexibility* or *InvestmentSkewness* value below the first quartile (above the third) as firms with easy (difficult) to disinvest hard assets, whereas we classify those with an *AssetReallocation* or *AssetLiquidity* value above the third (below the first) as firms with those same assets. See [Table A2](#) in [Appendix A](#) for more details about the disinvestment ability proxies. We compute the table entries by first averaging by sample month and distress portfolio and then by distress portfolio. The sample period is January 1986 to December 2020.

	Asset Inflexibility		Asset Reallocation		Asset Liquidity		Investment Skewness	
	Low	High	High	Low	High	Low	Low	High
Easy-to-Disinvest:	Yes	No	Yes	No	Yes	No	Yes	No
	1	2	3	4	5	6	7	8
High Distress	17.45	8.74	11.35	13.01	9.97	7.82	13.11	8.79
Moderate Distress	8.97	7.37	7.38	11.72	8.00	8.59	9.42	7.04
Low Distress	7.41	7.67	7.81	11.99	7.68	7.38	7.87	6.23
High-Low	10.04	1.07	3.54	1.02	2.29	0.44	5.25	2.56
# Deals (in 1,000s)	9	8	6	3	8	5	8	8

**Table 8: Disinvestment-Ability-Specific Stock, Bond, and Loan Regressions**

The table offers the results from [Fama and MacBeth \(1973\)](#) regressions of the excess returns of single stocks (Panel A), firm-specific bond portfolios (Panel B), and firm-specific loan portfolios (Panel C) over month  $t$  on two distress dummy variables and controls at the end of month  $t - 1$  separately estimated on subsamples conditioned on disinvestment ability. While Panels A and B focus on the stock-bond sample, Panel C concentrates on the stock-bond-loan-asset sample. The first and second subpanels in Panels B and C focus on standard and [Bartram et al. \(BGN\) \(2025\)](#) returns, respectively. We create the bond (loan) portfolios by forming value-weighted portfolios of all outstanding bonds (loans) by firm. The high (low) disinvestment-ability subsample contains firms with an *AssetInflexibility* or *InvestmentSkewness* value below the first (above the third) quartile or an *AssetReallocation* or *AssetLiquidity* above the third (below the first). The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if [Campbell et al. \(2008\)](#) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. See Tables [A1](#) and [A2](#) for more details about the controls and the disinvestment ability proxies, respectively. Plain numbers are monthly premium estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics calculated with a twelve-month lag length. To be concise, the table does not report the control estimates and  $t$ -statistics. While the sample period for the stock-bond sample is January 1986 to December 2020, the sample period for the stock-bond-loan-asset sample is August 1999 to April 2020.

	Asset Inflexibility		Asset Reallocation		Asset Liquidity		Investment Skewness	
	Low	High	High	Low	High	Low	Low	High
Disinvestable:	Yes	No	Yes	No	Yes	No	Yes	No
	1	2	3	4	5	6	7	8
Panel A: Stock Returns								
<i>HighDistress</i>	-0.59	-0.88	-0.15	-1.30	-0.58	-0.40	-0.43	-0.62
	[-1.81]	[-3.12]	[-0.30]	[-2.70]	[-1.74]	[-1.18]	[-1.28]	[-1.47]
<i>LowDistress</i>	-0.08	-0.19	-0.13	-0.43	-0.11	-0.34	-0.25	-0.45
	[-0.78]	[-2.08]	[-0.96]	[-2.47]	[-1.07]	[-3.54]	[-1.95]	[-4.95]
Controls	S	S	S	S	S	S	S	S
Panel B: Firm-Level Bond Returns								
Panel B.1: Month-End to Month-End Bond Returns								
<i>HighDistress</i>	-0.29	-0.09	-0.51	-0.17	-0.27	-0.07	-0.43	-0.17
	[-3.24]	[-0.74]	[-2.68]	[-1.60]	[-2.24]	[-0.78]	[-4.71]	[-1.98]
<i>LowDistress</i>	0.10	0.07	0.36	0.08	0.10	0.07	0.09	0.04
	[3.53]	[3.54]	[1.55]	[2.95]	[2.97]	[3.05]	[2.83]	[1.79]
Panel B.2: <a href="#">Bartram et al. (2025)</a> Bond Returns								
<i>HighDistress</i>	-0.28	-0.02	-0.50	-0.18	-0.26	-0.07	-0.42	-0.16
	[-3.05]	[-0.14]	[-2.68]	[-1.74]	[-2.25]	[-0.78]	[-4.57]	[-2.00]
<i>LowDistress</i>	0.09	0.07	0.36	0.08	0.09	0.06	0.08	0.04
	[3.29]	[3.44]	[1.54]	[2.96]	[2.93]	[2.83]	[2.69]	[1.72]
Controls	SB	SB	SB	SB	SB	SB	SB	SB

(continued on next page)

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Panel C: Firm-Level Loan Returns

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Panel C.1: Month-End to Month-End Loan Returns

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<i>HighDistress</i>	-0.48 [-2.24]	-0.40 [-2.03]	-0.39 [-2.11]	-0.26 [-1.30]	-0.35 [-1.96]	-0.32 [-1.32]	-0.69 [-2.94]	-0.14 [-0.94]
<i>LowDistress</i>	0.03 [0.35]	0.01 [0.26]	-0.05 [-0.41]	-0.08 [-0.98]	0.00 [-0.01]	0.01 [0.18]	-0.05 [-0.44]	0.12 [1.68]

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Panel C.2: [Bartram et al. \(2025\)](#) Loan Returns

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<i>HighDistress</i>	-0.45 [-1.97]	-0.21 [-1.08]	-0.41 [-1.77]	-0.19 [-1.02]	-0.31 [-1.73]	-0.43 [-2.35]	-0.68 [-2.71]	-0.16 [-1.25]
<i>LowDistress</i>	0.03 [0.44]	0.05 [1.23]	-0.04 [-0.25]	-0.13 [-1.41]	0.00 [0.05]	0.03 [0.64]	0.03 [0.43]	0.11 [1.71]
Controls	SL							

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**Table 9: Volatility-Specific Stock, Bond, and Loan Regressions**

The table offers the results from [Fama and MacBeth \(1973\)](#) regressions of the excess returns of the single stocks (Panel A), firm-specific bond portfolios (Panel B), and firm-specific loan portfolios (Panel C) of high or low disinvestment-ability firms over month  $t$  on two distress dummy variables and controls at the end of month  $t - 1$  separately estimated on subsamples conditioned on stock volatility. While Panels A and B focus on the stock-bond sample, Panel C concentrates on the stock-bond-loan-asset sample. The first and second subpanels in Panels B and C focus on standard and [Bartram et al. \(BGN\) \(2025\)](#) returns, respectively. While Panel A considers only firms with an *AssetInflexibility* or *InvestmentSkewness* value above the third quartile or an *AssetReallocation* or *AssetLiquidity* below the first (low-disinvestment-ability firms), Panels B and C consider only those with an *AssetInflexibility* or *InvestmentSkewness* value below the first quartile or an *AssetReallocation* or *AssetLiquidity* above the third (high-ability firms). We calculate stock volatility as the annualized standard deviation of the residual from the [Fama and French \(1993\)](#) three-factor model estimated over monthly data over the prior two years. We create the bond (loan) portfolios by forming value-weighted portfolios of all outstanding bonds (loans) by firm. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if [Campbell et al. \(2008\)](#) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. See [Tables A1 and A2](#) for more details about the controls and the disinvestment ability proxies, respectively. Plain numbers are monthly premium estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics calculated with a twelve-month lag length. To be concise, the table does not report the control estimates and  $t$ -statistics. While the sample period for the stock-bond sample is January 1986 to December 2020, the sample period for the stock-bond-loan-asset sample is August 1999 to April 2020.

	Historical Stock Volatility							
	High	Low	High	Low	High	Low	High	Low
	Asset Inflexibility	Asset Inflexibility	Asset Reallocation	Asset Reallocation	Asset Liquidity	Asset Liquidity	Investment Skewness	Investment Skewness
	1	2	3	4	5	6	7	8
Panel A: Hard-to-Disinvest-Asset (IRREV) Stocks								
<i>HighDistress</i>	-0.73	-0.24	-1.00	-0.11	-0.46	0.13	-0.72	-0.02
	[-2.04]	[-0.54]	[-1.91]	[-0.23]	[-1.15]	[0.45]	[-1.53]	[-0.05]
<i>LowDistress</i>	-0.13	-0.23	-0.31	-0.32	-0.06	-0.41	-0.29	-0.52
	[-0.90]	[-2.29]	[-1.02]	[-2.13]	[-0.34]	[-4.13]	[-1.77]	[-5.96]
Controls	S	S	S	S	S	S	S	S
Panel B: Easy-to-Disinvest-Asset (REV) Bonds								
Panel B.1: Month-End to Month-End Bond Returns								
<i>HighDistress</i>	-0.26	0.02	-0.57	-0.02	-0.37	-0.03	-0.31	-0.01
	[-2.95]	[0.48]	[-2.26]	[-0.20]	[-2.21]	[-0.41]	[-2.93]	[-0.09]
<i>LowDistress</i>	0.12	0.08	0.03	0.14	0.04	0.05	0.09	0.11
	[2.78]	[3.15]	[0.29]	[1.83]	[0.41]	[1.41]	[2.16]	[2.65]
Panel B.2: <a href="#">Bartram et al. (2025)</a> Bond Returns								
<i>HighDistress</i>	-0.25	0.01	-0.47	-0.04	-0.37	-0.02	-0.34	0.00
	[-2.80]	[0.19]	[-1.88]	[-0.31]	[-2.24]	[-0.30]	[-3.45]	[-0.00]
<i>LowDistress</i>	0.09	0.07	0.04	0.14	0.03	0.04	0.06	0.11
	[2.16]	[2.86]	[0.39]	[1.84]	[0.36]	[1.29]	[1.14]	[2.60]
Controls	SB	SB	SB	SB	SB	SB	SB	SB

(continued on next page)

Panel C: Easy-to-Disinvest-Asset (REV) Loans								
Panel C.1: Month-End to Month-End Loan Returns								
<i>HighDistress</i>	-0.34	-0.15	0.00	-0.20	-0.55	0.00	-0.68	-0.12
	[-2.21]	[-0.93]	[-0.00]	[-1.22]	[-2.29]	[0.03]	[-2.76]	[-1.52]
<i>LowDistress</i>	0.03	0.18	0.17	0.11	-0.22	0.05	0.16	-0.24
	[0.27]	[0.82]	[1.10]	[0.80]	[-1.63]	[1.12]	[1.17]	[-1.26]
Panel C.2: <a href="#">Bartram et al. (2025)</a> Loan Return								
<i>HighDistress</i>	-0.34	-0.16	-0.14	-0.18	-0.56	0.03	-0.77	-0.04
	[-1.80]	[-1.08]	[-0.88]	[-1.15]	[-2.42]	[0.78]	[-3.04]	[-0.59]
<i>LowDistress</i>	-0.04	0.18	-0.07	0.11	-0.15	0.03	0.11	-0.06
	[-0.49]	[0.84]	[-0.63]	[0.65]	[-1.05]	[0.57]	[0.98]	[-0.59]
Controls	SL	SL	SL	SL	SL	SL	SL	SL

## A. Additional Variable-Calculation Details

In this appendix, we offer details on how we calculate (i) bond returns, (ii) [Campbell et al.’s \(2008\)](#) default risk predictors, and (iii) our controls. At the end, we also offer tables summarizing the definitions of our controls ([Table A1](#)) and disinvestment ability proxies ([Table A2](#)).

### A.1. Calculating NAIC and TRACE Bond Returns

We use equation (1) to calculate bond returns from NAIC and TRACE data. To that end, we require the daily bond price, the accrued interest, and the coupon payment. We follow the literature in calculating those variables. To be specific, we compute a bond’s daily price from TRACE as a trading-volume-weighted average of its intra-day prices, minimizing confounding effects arising from the bid-ask spread. To calculate the accrued interest from TRACE, we first compute the daily coupon rate as the coupon rate divided by 360 if a bond’s day-count basis is “30/360” or “ACT/360” and as that same rate divided by the actual number of calendar days per year if it is “ACT/ACT.” We next count the calendar days between the current month-end  $t$  and the previous coupon date, assuming a number of days per calendar month equal to 30 if the day-count basis is “30/360” and equal to the actual number of days if “ACT/360” or “ACT/ACT.” We use the first coupon date and the coupon frequency to infer when coupons are paid. We finally calculate the accrued interest  $AI$  as the daily coupon rate times the number of days between current month-end  $t$  and previous coupon date.

We compute two alternative bond returns from NAIC and TRACE. Defining the start (end) of a month as its first (last) five trading days, the first ranges from the start of month  $t$  to the end of that month, while the second ranges from the start of month  $t$  to the start of month  $t + 1$ . If there are multiple non-missing daily prices over a five-day (start or end of month) period, we always

choose that closest to the turn of the month. If we can calculate both alternatives, we always pick that from start of month  $t$  to start of month  $t + 1$ .<sup>26</sup>

## A.2. Calculating Campbell et al.’s (2008) Default Risk Predictors

We use Campbell et al.’s (2008) hazard model to measure distress risk, projecting a dummy variable equal to one if a firm defaults, files for bankruptcy, or is delisted for performance reasons over the month twelve months from the current and else zero, *Failure*, on distress risk predictors measured at the end of the current month (recall equation (4) in Section II.B). The distress risk predictors are *NIMTA*, *TLMTA*, *CASHMTA*, *MB*, *SIGMA*, *EXRET*, *SIZE*, and *PRICE*. *NIMTA* is 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* is the ratio of the book value of total liabilities to those same assets. *CASHMTA* is the sum of cash and short-term assets to those assets. *MB* is the market-to-book ratio, where we add 10% of the difference between the market and book value of equity to the book value of equity and set book values of equity which continue to be negative to \$1. *EXRET* is the monthly log stock return in excess of the monthly log S&P 500 return. *SIGMA* is a stock’s volatility obtained from daily data over the prior three months.<sup>27</sup> *SIZE* is the log ratio of a stock’s market capitalization to the S&P 500’s total market capitalization. Finally, *PRICE* is the log stock price truncated from above at \$15.

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<sup>26</sup>We do not study the return from end of month  $t - 1$  to the end of month  $t$ . The reason is that its calculation period overlaps with that used to compute our distress proxy, inducing look-ahead bias.

<sup>27</sup>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.

To enhance the timeliness of the predictors, we follow [Campbell et al. \(2008\)](#) in using quarterly accounting data in our calculations, assuming that the accounting values become publicly available with a two-month reporting gap (i.e., two months after the end of the fiscal quarter). To guard against outliers, we winsorize the distress risk predictors at the 5th and 95th percentiles.

### **A.3. Calculating Our Control Variables**

Our portfolio sorts control for systematic risk by calculating the intercept (“alpha”) from a time-series regression of a portfolio’s excess return (i.e., its return minus the risk-free rate) on the factors from alternative factor models. As we said, we use the FF3S, the FF5S, and the FF6S models for our stock portfolios. Intuitively, the FF3S model contains as factors the excess stock market return (MKT) and the returns of spread portfolios formed on stock size (SMB) and the book-to-market ratio (HML). The FF5S model then adds the returns of spread portfolio formed on asset growth (CMA) and profitability (RMW). Finally, the FF6S model adds the return of a spread portfolio formed on the intermediate-term past return (MOM). See Kenneth French’s website for more details about the stock factors. We use the FF5SB, SB8, and SB14 models for our bond and loan portfolios. The FF5SB model contains the MKT, SMB, and HML stock factors plus the returns of a corporate bond spread portfolio formed on default risk (DEF) and a government bond portfolio formed on maturity time (TERM). See Amit Goyal’s website for more details about the DEF and TERM factors. The SB8 model adds the returns of a value-weighted portfolio of corporate bonds with a rating equal to or above BBB– (IGBMKT) and a value-weighted portfolio of corporate bonds with a rating below BBB– (SGBMKT) and the return of a corporate bond spread portfolio formed on the intermediate-term past return (BMOM). Finally, the SB14 model adds the returns of corporate bond spread portfolios

formed on the bond book-to-market ratio (BHML), the prior-month return (BSTR), the long-term past return (BLTR), duration (BDUR), carry (BCAR), and earnings announcement drift (BPEAD). See the Open Source Bond Asset Pricing website for more details about the BMOM, BHML, BSTR, BLTR, BDUR, BCAR, and BPEAD factors. We add the CMA, RMW, and MOM stock factors to the FF5SB, SB8, and SB14 model factors to create the SB8, SB11, and SB17 models to control for the systematic risk of our firm-asset portfolios, respectively. We obtain data on all the factors of those factor models except IGBMKT and SGBMKT (which we calculate ourselves) from the cited websites.<sup>28</sup>

Our FM regressions rely on both factor exposures and characteristics as control variables. In the stock regressions, we include a stock's exposure to the excess stock market return (*MarketBeta*) and its log market size (*MarketSize*), book-to-market ratio (*BookToMarket*), past eleven-month return (*Momentum*), asset growth (*AssetGrowth*), and profitability (*Profitability*). In the bond regressions, we add a bond's exposure to the excess bond market return (*BondMarketBeta*) and its amount outstanding (*BondSize*), time-to-maturity (*BondMaturity*), most recent credit rating (*BondCreditRating*), 5% Value-at-Risk (*BondDownsideRisk*), and short-term past return (*BondReversal*). In contrast, the loan regressions add the loan's market value (*LoanSize*) and its time-to-maturity (*LoanMaturity*). We estimate the exposures from rolling window regressions over the past 36 months of monthly data. We further always winsorize the factor exposures and characteristics at the 1st and 99th percentiles per sample month. See Table A1 at the end of this appendix for details.

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<sup>28</sup>The URL addresses of Ken French's and Amit Goyal's websites are: <<https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>> and <<https://sites.google.com/view/agoyal145>>, respectively. Conversely, the URL of the Open Source Bond Asset Pricing website is: <<https://openbondassetpricing.com/>>.

**Table A1: Regression Control Variables**

The table defines the control variables used in our regressions. We update the controls indexed by “M” on a monthly basis and use their values to condition stock, bond, loan, and firm asset returns over the next month. We update those indexed by “A” on an annual basis and use their values to condition those same returns over the period from July of year  $t$  to June of year  $t + 1$ . We show the data-provider mnemonics in parentheses.

Variable Name	Variable Definition
Panel A: Stock Control Variables	
<i>MarketBeta</i> (M)	Slope coefficient from a time-series regression of a stock’s excess return on the value-weighted CRSP index excess return (vwretd) estimated over the prior 36 months of monthly data (see <a href="#">Fama and MacBeth (1973)</a> and <a href="#">McLean and Pontiff (2016)</a> ).
<i>MarketSize</i> (A)	Log stock size (abs(prc) $\times$ shrout) at the end of June of year $t$ (see <a href="#">Fama and French (1992)</a> ).
<i>BookToMarket</i> (A)	Log of the ratio of the book value of equity to the market value of equity (abs(prc) $\times$ shrout), where the book value of equity is equal to total assets (at) minus total liabilities (lt) plus deferred taxes (txditc, zero if missing) minus preferred stock (pstkl, pstkrv, prfstck, or zero; in that order of availability). We take the values of all variables used in the calculation from the fiscal year-end in calendar year $t - 1$ (see <a href="#">Fama and French (1992)</a> ).
<i>Momentum</i> (M)	A stock’s dollar return (ret) compounded over the prior twelve months of monthly data, but excluding the most recent month (see <a href="#">Jegadeesh and Titman (1993)</a> ).
<i>AssetGrowth</i> (A)	Log of the gross change in total assets (at) from the fiscal year end in calendar year $t - 2$ to the fiscal year end in calendar year $t - 1$ (see <a href="#">Cooper, Gulen, and Schill (2008)</a> ).
<i>Profitability</i> (A)	Ratio of sales (sale) net of costs of goods sold (cogs), selling, general, and administrative expenses (xsge), and interest expenses (xint) to the book value of equity, where the book value of equity is total assets (at) less total liabilities (lt) plus deferred taxes (txditc, zero if missing) less preferred stock (pstkl, pstkrv, prfstck, or zero; in that order of availability). We take the values of all variables used in the calculation from the fiscal year end in calendar year $t - 1$ (see <a href="#">Fama and French (2008)</a> ).
Panel B: Bond Control Variables	
<i>BondMarketBeta</i> (M)	Slope coefficient from a time-series regression of a bond’s excess return on the excess return of a value-weighted portfolio containing all our sample bonds estimated over the prior 36 months of monthly data (see <a href="#">Bai, Bali, and Wen (2019)</a> ).
<i>BondSize</i> (M)	Log bond size ((bond price plus accrued interest scaled by bond principal amount) times (bond notional amount outstanding/bond principal amount)) at the end of month $t - 1$ .
<i>BondMaturity</i> (M)	Log of a bond’s years-to-maturity.
<i>BondCreditRating</i>	Numerical value for a bond’s most recent credit rating, with a value of one indicating a AAA/Aaa rating, a value of two indicating a AA+/Aa1 rating, and so on. A value of 21 finally indicates a D/C rating. When both S&P and Moody’s provide a rating, we take the average of the two corresponding numerical values (see <a href="#">Bai et al. (2019)</a> ).
<i>BondDownsideRisk</i> (M)	Minus one times the second lowest bond return over the prior 36 months of monthly data (“5% Value-at-Risk (VaR);” see <a href="#">Bai et al. (2019)</a> ).
<i>BondReversal</i> (M)	Monthly bond return (see <a href="#">Bai et al. (2019)</a> ).
Panel C: Loan Control Variables	
<i>LoanSize</i> (M)	Log loan size (loan notional amount outstanding $\times$ loan price per dollar (par price) + accrued interest on loan notional amount outstanding).
<i>LoanMaturity</i> (M)	Log of a loan’s years-to-maturity.

**Table A2: Disinvestment Ability Proxy Variables**

The table defines the disinvestment ability proxies used to measure the ease with which a firm can disinvest its hard assets. We update the variables indexed by “A” on an annual basis and use their values to condition those same returns over the period from July of year  $t$  to June of year  $t + 1$ . Conversely, we do not update the variables indexed by “S,” only relying on their full-sample values. We show the data-provider mnemonics in parentheses.

Variable Name	Variable Definition
<i>AssetInflexibility</i> (A)	The difference between the maximum and the minimum of an industry’s ratio of total operating costs to total sales (saleq) scaled by the standard deviation of the change in the log of the sales-to-assets ratio calculated using quarterly data until the end of the fiscal year in the prior calendar year. We define total operating costs as the sum of costs of good sold (cogsq) and selling, general, and administrative (xsgaq) expenses. We define the industries using Fama and French’s 49 industries (see <a href="#">Gu et al. (2018)</a> ).
<i>AssetReallocation</i> (A)	Ratio of the sum of acquisitions (aqc) and sales of property, plant, and equipment (sppe) scaled by total assets calculated using data from the fiscal year ending in the prior calendar year (see <a href="#">Eisfeldt and Rampini (2006)</a> ).
<i>AssetLiquidity</i> (A)	Number of deals in a three-digit SIC industry over the prior calendar year, where deals constitute asset acquisitions of, acquisitions of, and mergers with firms operating in that industry. The deal data are from SDC Platinum (see <a href="#">Schlingemann et al. (2002)</a> ).
<i>InvestmentSkewness</i> (S)	Time-series skewness of an industry’s annual total gross investment rate, defined as the net investment rate plus depreciation rate. The net investment rate is the change in net property, plant, and equipment $((\text{ppent}_{t+1} - \text{ppent}_t)/\text{ppent}_t)$ , while the depreciation rate is depreciation and amortization (dp) minus the amortization of intangibles (am, zero if missing) scaled by net property, plant, and equipment. We define the industries using Fama and French’s 49 industries. To minimize estimation noise, we calculate the estimates using the longest possible sample period (see <a href="#">Bai et al. (2024)</a> ).

Internet Appendix:

# Real Disinvestments and the Distress Anomaly: Evidence from Stocks, Bonds, and Loans

AUTHOR 1, AUTHOR 2, and AUTHOR 3

In this Internet Appendix, we offer empirical evidence and mathematical derivations omitted from our main paper. In Section [IA.1](#), we start off with looking into the coverage and quality of our bond and loan price data in the stock-bond and stock-bond-loan-asset samples (Tables [IA.1](#) to [IA.3](#) and Figures [IA.1](#) and [IA.2](#)). Section [IA.2](#) explores the characteristics and beta loadings of the stock and bond portfolios in the stock-bond sample and their long-horizon pricing (Tables [IA.4](#) and [IA.5](#) and Figure [IA.3](#)). Section [IA.3](#) investigates single-bond portfolios double-sorted on distress and bond ratings (Table [IA.6](#)). In Section [IA.4](#), we consider the characteristics and beta loadings of the stock, bond, loan, and firm-asset portfolios in the stock-bond-loan-asset sample and their long-horizon pricing (Tables [IA.7](#) and [IA.8](#) and Figure [IA.4](#)). Section [IA.5](#) offers the results from several robustness tests on the pricing of distress risk in stocks, bonds, loans, and firm-assets, shedding light on the effects of matrix prices (Tables [IA.9](#) to [IA.12](#)), illiquidity and liquidity risk (same tables), changes in bond or loan ownership spurred by mergers and acquisitions (M&As; Tables [IA.13](#) to [IA.16](#)), and omitted and/or underrepresented asset classes in our asset return calculations (Tables [IA.17](#) to [IA.20](#) and Figure [IA.5](#)). In Section [IA.6](#), we use [Fan and Sundaresan's \(2000\)](#) model to formally demonstrate that [Garlappi et al.'s \(2008\)](#) and [Garlappi and Yan's \(2011\)](#) shareholder advantage theory cannot explain a negative debt distress premium. Finally, Section [IA.7](#) derives the quasi-closed-form solutions for our real options model in Section [IV](#) of our main paper, offers details about the Monte Carlo

simulations used to derive stock and debt values from that model, and gives comparative statics for the disinvestment ability-expected stock or debt return results extracted from the model.

## IA.1 Sample Data Coverage and Quality

In this section, we replicate all the exercises in the appendixes and online appendixes of [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#) to corroborate that our bond and loan samples are reasonably comprehensive and that the prices in them are of a high quality. Doing so is important since our bond sample mixes matrix prices from Lehman Brothers, Datastream, and ICE, quotes from Lehman Brothers and Datastream, and transaction prices from NAIC and TRACE (see Section 1 in our main paper). Conversely, our loan sample mixes quotes from LoanConnector and transaction prices from CLO-i (see Section 2 in that same paper). Given that, it is unclear to what extent the bond and loan samples span the CRSP-Compustat universe, the bond sample the Mergent FISD universe, and the loan sample the Dealscan universe. Moreover, as especially matrix prices but also quotes can be of a low quality, it is unclear to what extent our samples suffer from price staleness.

We first look into the coverage of our stock-bond and stock-bond-loan-asset samples. We then evaluate the quality of the stock, bond, and loan data, especially with respect to staleness.

### IA.1.1. Bond and Loan Data Coverage

We now investigate the coverage of our stock-bond and stock-bond-loan-asset samples. To that end, we first replicate the sample-coverage statistics in Table A.1 of [Choi and Richardson \(2016\)](#) benchmarking their stock-bond sample firms against the CRSP-Compustat universe for our two samples.<sup>1</sup> More specifically, Internet Appendix Table [IA.1](#) gives the number of observations, mean and median market assets, and median book and market leverage for several samples in Panel A and for several credit-rating-based subsamples in Panel B. In addition, Panel A also reports the median proportion of a firm's debt book value (the sum of short and long-term debt) covered by the outstanding bond balance

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<sup>1</sup>We omit their statistics for the sample of bonds with a non-missing implied volatility from Optionmetrics (the final column in Panel A of their table) since we do not require that variable for our purposes.

in the stock-bond sample and the outstanding bond plus loan balance in the stock-bond-loan-asset sample. While the samples in Panel A are the entire CRSP-Compustat universe, the sub-universes of levered and non-levered firms, the entire stock-bond firm sample and the subsample with assets above \$100 million, and the entire stock-bond-loan-asset firm sample and the subsample with assets above \$100 million, the subsamples in Panel B are based on the stock-bond and the stock-bond-loan-asset samples. In line with [Choi and Richardson \(2016\)](#), we calculate market assets as the market equity value plus the book debt value and use entity ratings to form the subsamples in Panel B.

Despite the differences in data sources and sample periods, Internet Appendix Table [IA.1](#) yields bond-sample results in close agreement with those obtained in Table A.1 in [Choi and Richardson \(2016\)](#).<sup>2</sup> In particular, we also find that our bond sample is a relatively small (about 15%) subsample of the entire CRSP-Compustat universe featuring larger (mean market assets: \$21-vs.-\$4 billion) and more levered (median market leverage: 1.52-vs.-1.24) firms (see Panel A). In accordance, the corresponding numbers in [Choi and Richardson \(2016\)](#) are about 19%, \$8.3-vs.-\$2.0 billion,<sup>3</sup> and 1.45-vs.-1.18, respectively. The median proportion of book debt captured by the outstanding bond balances of our stock-bond sample firms is about 76%, also not too distant from the about 69% calculated by them. Switching to the ratings-based subsamples of our stock-bond sample in Panel B, it is obvious that while market asset values tend to be higher for better-rated firms, leverage and the proportion of book debt covered by outstanding bond balances tend to be lower for them, also in agreement with the statistics in Panel B of Table A.1 in [Choi and Richardson \(2016\)](#).

Notwithstanding the similarities, a striking difference between Internet Appendix Table [IA.1](#) and [Choi and Richardson's \(2016\)](#) Table A.1 lies in the number of observations in our and their stock-bond samples. To be specific, while our stock-bond sample period is not only more recent (which is relevant since data coverage usually rises over time) but also three years longer than theirs, the number of observations is about the same (284k-vs.-286k in our-vs.-their sample, respectively). The reason,

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<sup>2</sup>In comparison to us, [Choi and Richardson \(2016\)](#) study bond prices from Lehman Brothers and the Thomson Reuters Bond Pricing Database (rather than Lehman Brothers, Datastream, ICE, NAIC, and TRACE) over the sample period from January 1980 to December 2012 (rather than January 1986 to December 2020).

<sup>3</sup>Note that since we report nominal (and not real) dollar values, it is unsurprising that our dollar values are higher than theirs due to our more recent sample period. Notwithstanding, we both find that the average firm in the CRSP-Compustat universe is about 4-5 times smaller than the corresponding firm in the stock-bond sample.

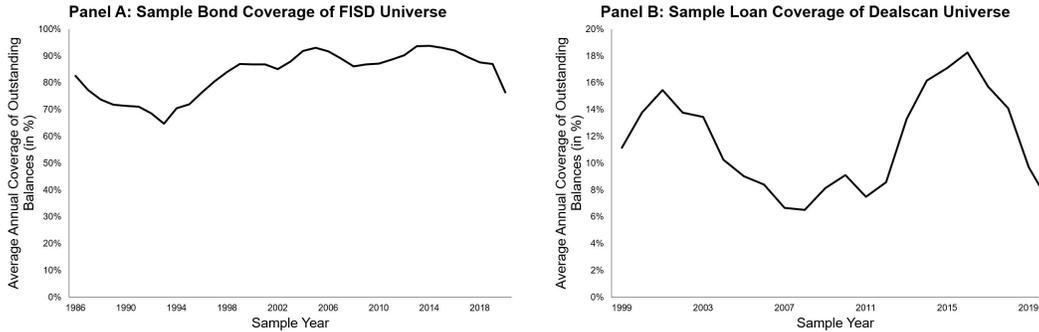
however, is that, in contrast to [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#), we follow many recent studies in the bond pricing literature (including, e.g., [Bai et al. \(2019\)](#), [Dick-Nielsen et al. \(2025\)](#), [Dickerson et al. \(2025\)](#), and [Bartram et al. \(2025\)](#)) in excluding “non-standard bonds” from our bond return calculations, only using their market capitalizations in our asset-return weights (see Sections 1 and 2 in our main paper). Also counting these non-standard bonds, the number of firm observations in our stock-bond sample shoots up to a more reasonable 556,174.

The stock-bond-loan-asset sample results in Internet Appendix Table [IA.1](#) often align with the stock-bond results. In particular, while the stock-bond-loan-asset sample is an even smaller (3%) subsample of the CRSP-Compustat universe, it is also skewed toward larger (mean market assets: \$12-vs.-\$4 billion) and more levered (1.72-vs.-1.24) firms (see Panel A).<sup>4</sup> More noteworthy, the median proportion of book debt captured by the outstanding bond plus loan balances of our stock-bond-loan-asset sample firms is 93%, close-to-identical to the 94% calculated by [Choi and Richardson \(2016\)](#). Looking into the ratings-based subsamples in Panel B, market asset values again tend to be higher for better-rated firms, but neither leverage nor the proportion of book debt covered by the outstanding bond and loan balances form a discernable pattern over the subsamples. Finally, the proportion of book debt covered by those balances consistently lies above 90% — except for the often thinly-populated AAA, AA, and A (39-82%) and the C (66%) rated subsamples.

We next compute the proportions of the aggregate outstanding bond balance in the Mergent FISD universe captured by the corresponding balance in our stock-bond sample and of the aggregate outstanding loan balance in the Dealscan universe captured by the corresponding balance in our stock-bond-loan-asset sample. We compute those proportions first by sample month and then average over time. In further agreement with both [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#), the bond proportion is 84%, not too far off from the 90% calculated in the two other studies. Averaging the sample-month-specific bond proportions by calendar year, Internet Appendix Figure [IA.1](#) shows that they initially decline from about 81% in 1986 to only about 65% in 1994, but then tend to increase

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<sup>4</sup>We are unable to contrast our stock-bond-loan-asset sample statistics with the corresponding statistics for [Choi and Richardson’s \(2016\)](#) bond-loan sample since [Choi and Richardson \(2016\)](#) do not separately report these. The reason is that they impute loan returns for firms with bonds but no traded loans from bond returns, so that their bond sample firms are identical to their bond-loan sample firms including those with imputed values.



**Figure IA.1: The Coverage of our Bond and Loan Sample Data**

The figure plots the proportions of the aggregate Mergent FISD outstanding bond balance captured by our sample bond data (Panel A) and of the aggregate Dealscan loan outstanding balance captured by our sample loan data (Panel B) over the 1986 to 2020 and the 1999 to 2020 sample periods, respectively. We calculate the proportions first by sample month and then average over year. We use only public firms and those bonds and loans not excluded by our sample filters (see Section 1 in our main paper) to calculate the aggregate balances.

over the remaining period (see Panel A). Conversely, the loan proportion is about 12%. Also averaging the sample-month-specific loan proportions by calendar year, Internet Appendix Figure IA.1 reveals that they lie between 6% and 18% over the sample period from 1999 to 2020 (see Panel B).

### IA.1.2. Data Quality

We next study the quality of our stock, bond, and loan data. As stressed in [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#), there may be concern that our bond and loan samples suffer from price staleness because the bond (loan) sample mixes matrix prices, quotes, and transaction prices (quotes and transaction prices). Yet, since matrix prices and quotes are only indicative, implying that investors cannot be sure that they can trade at them, it may be less urgent for dealers to update them in response to news. While we take the same steps as the above studies to minimize price staleness (i.e., we study monthly rather than higher-frequency returns and consider value as well as equally-weighted portfolios in all our tests), we now also look into the frequency of zero-price-change observations, autocorrelations and cross-correlations, and direct comparisons of matrix prices and quotes with transaction prices, to assess the magnitude of any remaining staleness. As demonstrated by [Scholes and Williams \(1977\)](#), staleness induces firm (portfolio) level returns to be negatively (positively)

autocorrelated. Also, it allows the returns of asset classes suffering less from staleness (as, e.g., stocks) to predict those of asset classes suffering more from it (as, e.g., bonds and loans).

We first look into the data quality of our stock-bond sample. Having done so, we then switch to investigating the data quality of our stock-bond-loan-asset sample.

#### *IA.1.2.1. The Stock-Bond Sample*

We start off with assessing the staleness in our stock-bond sample. To do so, we replicate Table C.1 in [Choi and Richardson \(2016\)](#) giving the proportion of zero bond-price-change observations (Panel A), the first three firm and (value-weighted) portfolio-level autocorrelations of our stock and bond returns (Panel B), and the cross-correlations of the bond return with the contemporaneous stock return and its first three lags and vice versa (Panel C) in our Internet Appendix Table [IA.2](#). We calculate each of the statistics for both the entire sample and credit-rating-based subsamples. Panel A of our table shows that the whole-sample proportion of zero-bond-price change observations at the single-bond or firm-portfolio<sup>5</sup> level is 1.7% and 6.2%, slightly lower than the corresponding numbers in [Choi and Richardson \(2016\)](#), 2.0% and 9.9%, all respectively. The slightly smaller proportions generated by our sample are perhaps unsurprising since, in contrast to their sample, ours is heavily (about 50%) skewed toward transaction prices which are less stale than quotes. Still, the proportion of zero-bond-price observations at the single-bond and firm-portfolio level markedly rise over the credit-rating subsamples in both of our samples, with the single-bond-level proportion, for example, increasing from 0.03% (1.9%) for the best to 4.8% (7.8%) for the worst-rated subsample in case of our (their) sample.

Looking into the autocorrelations in Panel B, our stock first-order autocorrelations at the firm (subpanel B.1) and portfolio (subpanel B.2) level are similar to [Choi and Richardson's \(2016\)](#). While the stock autocorrelation at the portfolio level, for instance, rises from  $-0.05$  to  $0.06$  over their credit-rating subsamples (average absolute value:  $0.06$ ), the corresponding rise over our subsamples is from  $-0.05$  to  $0.08$  (average absolute value:  $0.08$ ). More importantly, our firm and portfolio-level autocorrelations for bonds are also similar to theirs. While the average absolute first-order bond autocorrelation at the firm

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<sup>5</sup>The firm-portfolio statistic gives the proportion of firm-month observations for which at least one of all the bonds of some firm does not exhibit a price change over some month.

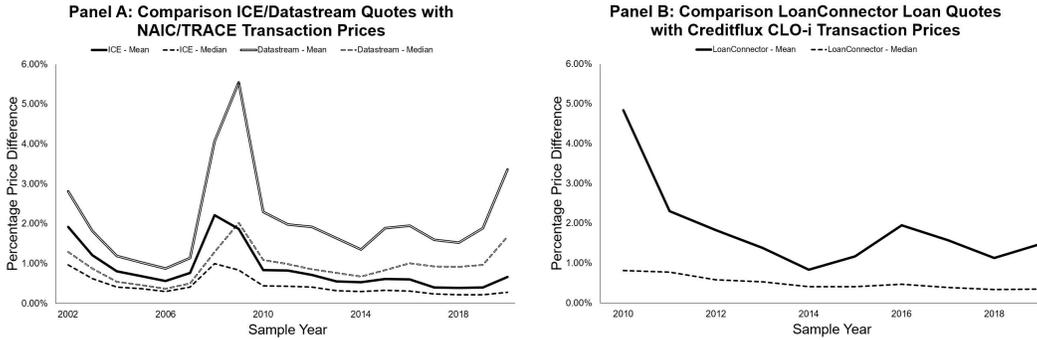
and portfolio level is, for example, 0.07 and 0.12 over their credit-rating subsamples, it is 0.06 and 0.10 over ours, all respectively. Interestingly, however, our bond autocorrelations are far more stable (i.e., increase far less) over those subsamples than theirs, especially at the portfolio level. The reason may once again be that, in contrast to their bond sample, ours contains a large proportion of transaction prices from NAIC and TRACE, and those prices are likely to be less susceptible to staleness.

Panel C confirms that the cross-correlations between stock and bond returns also align across [Choi and Richardson's \(2016\)](#) and our sample. While the average contemporaneous cross-correlation is, for example, 0.31 over their subsamples, it is 0.26 over ours. More importantly, while the absolute cross-correlation between bond returns and one-month-lagged stock returns is, for instance, on average 0.07 and never exceeds 0.15 over their subsamples, it is on average 0.06 and never exceeds 0.14 over ours. Given that even a cross-correlation of 0.15 implies that only 2.25% of the variations in bond returns can be forecasted with lagged stock returns, we can conclude that bond returns are close-to-unpredictable with stock returns in our and [Choi and Richardson's \(2016\)](#) sample.

We finally also contrast the bond matrix prices and quotes from ICE and Datastream with the corresponding transaction prices from NAIC and TRACE. To that end, we compute the absolute difference between those two type of prices scaled by the transaction price separately for the ICE and Datastream matrix prices and quotes.<sup>6</sup> We then take the mean or median difference by calendar year and average that over time. The overall mean and median absolute difference for the ICE prices are 0.87% and 0.44%, respectively, within the usual bid-ask spread of about one percent for liquid bonds (see [Choi and Richardson \(2016\)](#)). Strikingly, however, Internet Appendix Figure [IA.2](#) shows that the difference depends on the economic state, with it, for example, markedly rising to an average of about two percent at the onset of the global financial crisis (see Panel A). In contrast, the overall mean and median absolute difference for the Datastream prices are 2.10% and 0.95%, respectively, significantly higher than those for the ICE prices. Notwithstanding, the figure reveals that the Datastream differences also rise during crises. The worse quality of the Datastream bond data is unlikely to be an issue for us since only about 10% of our stock-bond sample observations

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<sup>6</sup>We are unable to perform a similar analysis on Lehman Brothers bond prices since the Lehman Brothers sample period does not overlap with the NAIC and TRACE sample periods.



**Figure IA.2: The Quality of our Bond and Loan Price Data**

The figure plots the mean and median absolute percentage differences between either our sample bond (Panel A) or loan (Panel B) quotes and the corresponding transaction prices over the sample periods from 2002 to 2020 and 2010 to 2020, respectively. While Panel A contrasts bond quotes from either ICE or Datastream with the corresponding transaction prices from both NAIC and TRACE, Panel B contrasts loan quotes from LoanConnector with the corresponding transaction prices from Creditflux CLO-i. We calculate the absolute percentage difference as the absolute price difference scaled by the transaction price. We then take the mean (solid line) or the median (broken line) by calendar year.

come from Datastream. Also, we later show in this Internet Appendix that replicating our main empirical tests using only bond transaction prices does not materially change our conclusions.

#### *IA.1.2.2. The Stock-Bond-Loan-Asset Sample*

We next consider the staleness in our stock-bond-loan-asset sample. To do so, we once again replicate Table C.1 in [Choi and Richardson \(2016\)](#) giving the proportion of zero-loan-price change observations (Panel A), the first three firm and (value-weighted) portfolio-level autocorrelations of our stock, bond, and loan returns (Panel B), and the cross-correlations between the bond or loan return and the contemporaneous stock return and its first three lags and vice versa (Panel C) in our Internet Appendix Table [IA.3](#). Panels B and C of our table corroborate that the stock and bond autocorrelations and their cross-correlations are highly similar across the stock-bond and stock-bond-loan-asset samples. While the whole-sample stock and bond firm-level autocorrelations are, for example,  $-0.01$  and  $-0.02$  in the stock-bond sample (average absolute values over the credit-rating subsamples:  $0.02$  and  $0.06$ ), the corresponding numbers for the stock-bond-loan-asset sample are  $-0.01$  and  $-0.04$  (average absolute values:  $0.06$  and  $0.07$ ), all respectively (contrast with Internet Appendix Table [IA.2](#)). Moreover, while

the cross-correlation between bond and one-month-lagged stock returns is 0.06 in the stock-bond sample, the corresponding number for the stock-bond-loan-asset sample is 0.08. Given those similarities in the stock and bond statistics, we focus on the loan statistics in the remainder of this section.

Panel A of Internet Appendix [IA.3](#) suggests that the loan prices in the stock-bond-loan-asset sample are far less likely to change than the bond prices in the stock-bond sample (contrast with Internet Appendix Table [IA.2](#)). More specifically, while there are only 1.7% zero-bond-price-change observations in the stock-bond sample, the corresponding number for loans in the stock-bond-loan-asset sample is a whopping 33.9%. Interestingly, the panel further demonstrates that the 33.9% is almost exclusively driven by an even higher proportion in the quotes (34.2%) rather than transaction price (1.0%) data. Notwithstanding, [Choi and Richardson \(2016\)](#) caution that a zero quote change does not necessarily indicate price staleness, but could — especially for financial claims at the top of the capital structure — simply imply stable interest rate and default risk expectations. Assuming that changes in expectations trigger trading, we find some support for that conjecture, showing that the proportion of zero-quote-change observations conditional on at least one trade over the month drops down to 0.2%. Surprisingly, and different from bonds, the proportion of zero-loan-price-change observations does not vividly increase over the credit-rating-based subsamples.

Looking into the autocorrelations in Panel B, the first-order loan autocorrelations at the firm-level are reasonably close-to-zero for the whole sample (0.06) and the subsamples (average absolute value: 0.07; see subpanel B.1). In contrast, the corresponding autocorrelations at the portfolio-level in subpanel B.2 are much more positive, with the whole-sample value being 0.43 and the subsample values rising from 0.02 for the best-rated to 0.32 for the worst-rated firms (average absolute value: 0.28). Conversely, the second-order autocorrelations at the portfolio level are much closer to zero again, with the whole-sample value being 0.14. The implication is thus that while the firm-level autocorrelations do not point to great staleness in our sample loan prices, the portfolio-level autocorrelations suggest that when the loan prices are updated in response to changes in interest rate and/or default risk expectations, those updates occur asynchronously over a period of about 1-2 months, especially for the loans of firms with weak credit ratings.

Studying the cross-correlations between stocks and loans in subpanel C.2 in Panel C reveals that the whole-sample contemporaneous cross-correlation is 0.22, not too far from the corresponding cross-correlations between stocks and bonds in the stock-bond (0.26) and stock-bond-loan-asset (0.30) sample (contrast with the stock-bond values in Panel C of Internet Appendix Table [IA.2](#) and the current table, respectively). Notwithstanding, the whole-sample cross-correlation of the loan return with the one-month-lagged stock return, 0.15, is higher than the corresponding cross-correlations of bond returns in either sample, 0.06-0.08. Also, while the cross-correlation of bond returns with lagged stock returns never exceeds 0.14 over the credit-rating subsamples in either sample, the corresponding loan cross-correlation can reach up to 0.22 for the C-rated-firm subsample. Despite that, even the cross-correlation of 0.22 implies that only 4.84% of the variations in loan returns can be predicted with one-month-lagged stock returns. We deem that number economically small.

We finally also contrast the loan quotes from LoanConnector with the corresponding transaction prices from CLO-i. While we conduct the comparisons analogously to the corresponding bond-price comparisons in Section [IA.1.2.1](#). of this Internet Appendix, we restrict our attention to the period from 2010 to 2020 since the CLO-i transaction-price cross-sections become reasonably wide only from the earlier year onward. The overall mean and median absolute differences are 1.85% and 0.51%, somewhat larger than the corresponding differences for the ICE bond prices, 0.87% and 0.44%, but lower than those for the Datastream bond prices, 2.10% and 0.95%, all respectively (contrast with the numbers in Section [IA.1.2.1](#).). Plotting the calendar-year mean and median differences over time, Figure [IA.2](#) in this Internet Appendix shows that they also depend on the economic state, with them again being particularly high at the end of the global financial crisis.

Overall, this section suggests that our stock-bond sample is an almost comprehensive sample of the Mergent FISD universe, while the stock-bond-loan-asset sample is a markedly smaller subsample of the Dealscan universe, with both, however, featuring larger firms with a higher financial leverage than the average CRSP-Compustat firm. Looking into the proportion of zero-price-change observations, autocorrelations and cross-correlations, and absolute price differences between matrix prices/quotes and transaction prices, it further reveals that our bond sample is of a reasonably high quality

comparable to that of the [Choi \(2013\)](#) and [Choi and Richardson \(2016\)](#) samples, whereas the loan sample is of a slightly weaker albeit (in our opinion) still acceptable quality.

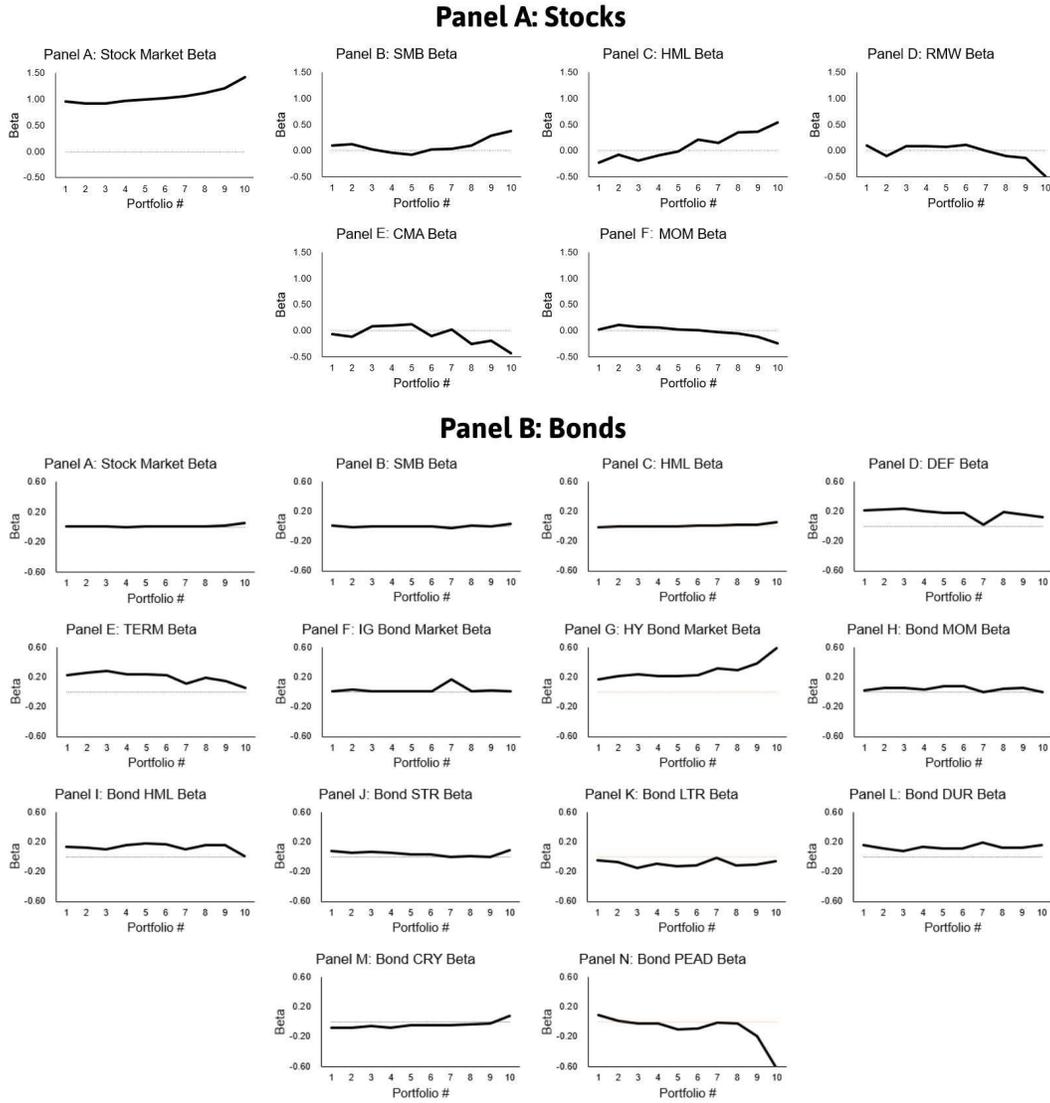
## IA.2 Characteristics, Beta Loadings, and Long-Horizon Distress Pricing of the Stock-Bond Portfolios

In this section, we investigate the characteristics, beta loadings, and the long-horizon distress premiums of the stock and bond distress portfolios in the stock-bond sample analyzed in Section B of our main paper. Starting with the characteristics, Internet Appendix Table IA.4 reports the mean characteristics of the stock (Panel A) and bond (Panel B) portfolios, first calculated by portfolio and sample month and then averaged over time. The stock characteristics include the market beta, market capitalization (“size”), the book-to-market ratio, momentum, asset growth, and profitability. The bond characteristics include the bond market beta, value-weighted average and aggregate bond market capitalization, the years-to-maturity, the credit rating, the coupon rate, downside risk, bond reversal, liquidity beta, and illiquidity. See Table A1 in Appendix A at the end of the main paper for details about the characteristics from the main paper. The coupon rate is the coupon-to-price ratio, the liquidity beta the loading on the orthogonalized aggregate signed volume coefficient from first-stage regressions (see [Lin et al. \(2011\)](#)), and illiquidity the daily-price-change autocovariance (see [Bao et al. \(2011\)](#)).<sup>7</sup>

Panel A of Internet Appendix Table IA.4 suggests that the mean characteristics of the stock portfolios align with those found in the literature (see, e.g., [Campbell et al. \(2008\)](#)). Specifically, highly distressed stocks tend to be small, unprofitable value stocks with a high market beta. Interestingly, however, both extremely high and low distress stocks tend to be high-investment loser stocks, creating an inverted U-shaped (U-shaped) relation between the intermediate-term past return (asset growth) and distress risk. Conversely, Panel B reveals that highly distressed bonds tend to be small (at least in terms of their value-weighted market capitalization), short-maturity-time, and high-coupon-rate bonds with low credit ratings. Moreover, they tend to have a high value-at-risk (as measured through

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<sup>7</sup>Since we require daily data to calculate the bond illiquidity and the bond liquidity risk variables, we highlight that we can calculate their mean values only over the sample period from July 2002 to December 2020.



**Figure IA.3: Factor Betas of the Stock-Bond Portfolios**

The figure shows the full-sample betas of the stock (Panel A) and firm-specific bond (Panel B) portfolios univariately sorted on distress risk on the FF6S and SB14 factor model factors, respectively. See Appendix A at the end of the main paper for more details about the construction of the factors included in the two factor models.

*DownsideRisk*), a low one-month-lagged past return (as captured by *Reversal*), a high liquidity beta, and a high illiquidity. Finally, both the bond market beta as well as the aggregate bond capitalization form, somewhat surprisingly, an inverted U-shape over the distress portfolios.

In Figure IA.3, we look into the full-sample beta loadings of the same stock (Panel A) and bond

(Panel B) distress portfolios on the six factors of the FF6S model and the 14 factors of the SB14 model, respectively. In agreement with the insight that a stock’s co-movement with some set of stocks often signals the stock’s identity (see [Fama and French \(2016\)](#)), the stock portfolio betas largely align with their mean characteristics. In particular, Panel A of the figure suggests that highly distressed stocks have high MKT, SMB, and HML but low RMW betas, in line with them being small, unprofitable value stocks with amplified market betas. Slightly different from the mean characteristics, the CMA betas, however, also decline over the distress portfolios, whereas the MOM betas are close-to-flat over them. Switching to the bond portfolios, Panel B reveals that, in contrast to the stock portfolio betas, the bond portfolio betas often do not strongly align with their mean characteristics, with most of them being virtually flat over the portfolios. The exceptions are the term-spread (TERM), the high-yield bond market portfolio (HY Bond Market), and the post earnings-announcement drift (Bond PEAD) betas. Consistent with highly distressed bonds having a short maturity time (low ratings and a high downside risk), the TERM (high-yield bond market) beta drops (rises) over the portfolios. Conversely, the bond PEAD beta markedly drops over the portfolios.

Finally, Internet Appendix Table [IA.5](#) tabulates the mean returns of the high-minus-low stock (Panel A) or bond (Panel B) distress spread portfolios in the stock-bond sample separately for each of the twelve months after portfolio formation, where we use both the standard (Ret=S) and the BGN (Ret=BGN) methodology to calculate bond returns. In the value and equally weighted sorts, we calculate the mean returns as the intercepts (“alphas”) obtained from regressing the value or equally weighted stock (bond) spread portfolio return on the contemporaneous returns of the FF6S (SB14) factor-model factors. In the FM regressions, we first regress the stock (bond) return on nine distress portfolio dummy variables indicating to which of the final nine portfolios the stock (bond) belongs (i.e., we omit the dummy for the first portfolio) and the controls also used in column (1) ((4)) of Table 3 of our main paper and measured until the start of the return month. We then set the mean return to the coefficient on the last distress portfolio dummy variable, capturing the mean spread return between distress deciles 10 and 1 after accounting for the controls. We stress that the value-weighted standard-return stock and bond results in Panels A and B of the table are identical

to the stock and bond results plotted in Figure 2 of our main paper, respectively.

The table corroborates our claim in the main paper that the stock and bond distress premiums in the stock-bond sample dissipate only slowly over time. In particular, while both premiums are close-to-consistently significant over the first six months after portfolio formation, they are also significant over single months over the last six. For example, the value-weighted standard-return bond premium is strongly significant over months  $t$  to  $t + 3$ , only weakly significant over month  $t + 4$ , strongly significant again over months  $t + 5$  and  $t + 6$ , but then insignificant over month  $t + 7$ . Given that distressed stocks and bonds tend to be smaller than their counterparts, the equally-weighted portfolios overweight distressed stocks and bonds relative to the value-weighted portfolios, often inducing the distress premiums obtained from them to remain significant for longer. In contrast to the portfolio sorts, the FM regressions suggest that the bond distress premium remains significant for only 2-3 months, presumably because they control for bond factors differently from the portfolio sorts. As always, the standard and BGN bond returns yield highly similar conclusions.

### IA.3 Portfolios Double-Sorted on Distress and Credit Ratings

[Avramov et al. \(2022\)](#) show that single corporate bonds with worse credit ratings earn lower mean returns than those with better ones, also pointing to a negative bond distress premium. Since [Hilscher and Wilson \(2017\)](#), however, reveal that ratings are a weak proxy for physical and more strongly reflect risk-neutral distress risk, it is unlikely that our evidence is driven by [Avramov et al.'s \(2022\)](#). To verify that claim, we next run a dependent double portfolio sort, either sorting our *single* sample bonds first into rating classes and then distress portfolios or vice versa. To be specific, we classify bonds with a most recent rating at the end of month  $t - 1$  of at least double-A as high investment grade, those with a rating below double-A but at least triple-B as low investment grade, and all others as speculative. Conversely, we sort them into distress portfolios according to the tercile breakpoints of the distress distribution on the same date. We value-weight the portfolios and hold them over month  $t$ . Within each rating (distress) portfolio, we form a spread portfolio long the top distress tercile (the

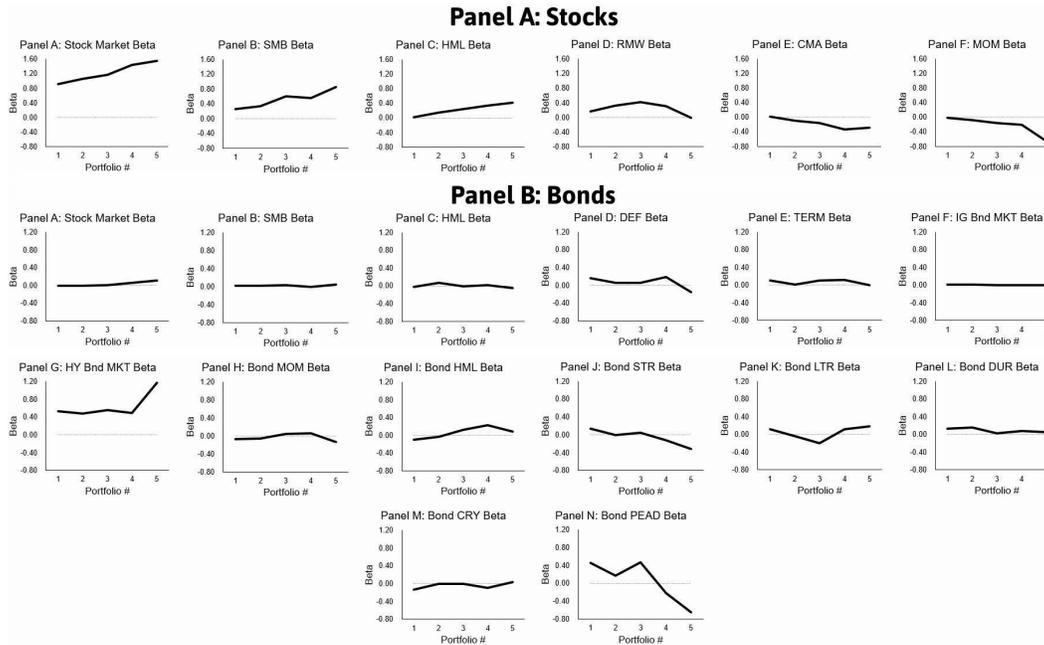
speculative grade) portfolio and short the bottom tercile (the high investment grade) portfolio.

Internet Appendix Table [IA.6](#) gives the double portfolio sort results. While Panel A focuses on the sort first into rating and then distress portfolios, Panel B examines the reverse sort. Conversely, while columns (1), (3), and (5) report the mean single-bond numbers, the plain numbers in columns (2), (4), and (6) are monthly SB14 alphas (in %) and those in square brackets Newey-West (1987)  $t$ -statistics. The table suggests that controlling for ratings, the SB14 alphas still drop significantly over the distress portfolios. Looking into low-investment-grade bonds in columns (3) and (4) of Panel A, we, for example, find that the SB14 alpha still decreases by 0.11% ( $t$ -statistic:  $-3.62$ ). Conversely, controlling for distress risk, the SB14 alphas are either *higher* for worse-rated bonds or do not relate to ratings. Considering the middle default tercile in columns (3) and (4) of Panel B, we, for example, find that the SB14 alpha changes by a mere 0.03% ( $t$ -statistic: 0.34). The key lesson to take away is that while our results subsume those of [Avramov et al. \(2022\)](#), theirs do not subsume ours.

## IA.4 Characteristics, Beta Loadings, and Long-Horizon Distress Premiums of the Stock-Bond-Loan-Asset Portfolios

In this section, we study the characteristics, beta loadings, and the long-horizon distress premiums of the stock, bond, loan, and firm-asset distress portfolios in the stock-bond-loan-asset sample analyzed in Section [C](#) of our main paper. Starting with the characteristics, Internet Appendix Table [IA.7](#) reports the mean characteristics of the stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) portfolios, first calculated by portfolio and sample month and then averaged over time. While the stock and bond characteristics in Panels A and B are the same as those in the same panels in Internet Appendix Table [IA.4](#), respectively, the loan characteristics in Panel C include the value-weighted average and aggregate loan capitalization (“size”) and the years-to-maturity and the firm-asset characteristics in Panel D the aggregate firm-asset capitalization. See Section [IA.2](#) in this Internet Appendix and the references in there for details about the characteristics.

Panels A and B of Internet Appendix Table [IA.7](#) suggest that the stock-bond-loan-asset sample

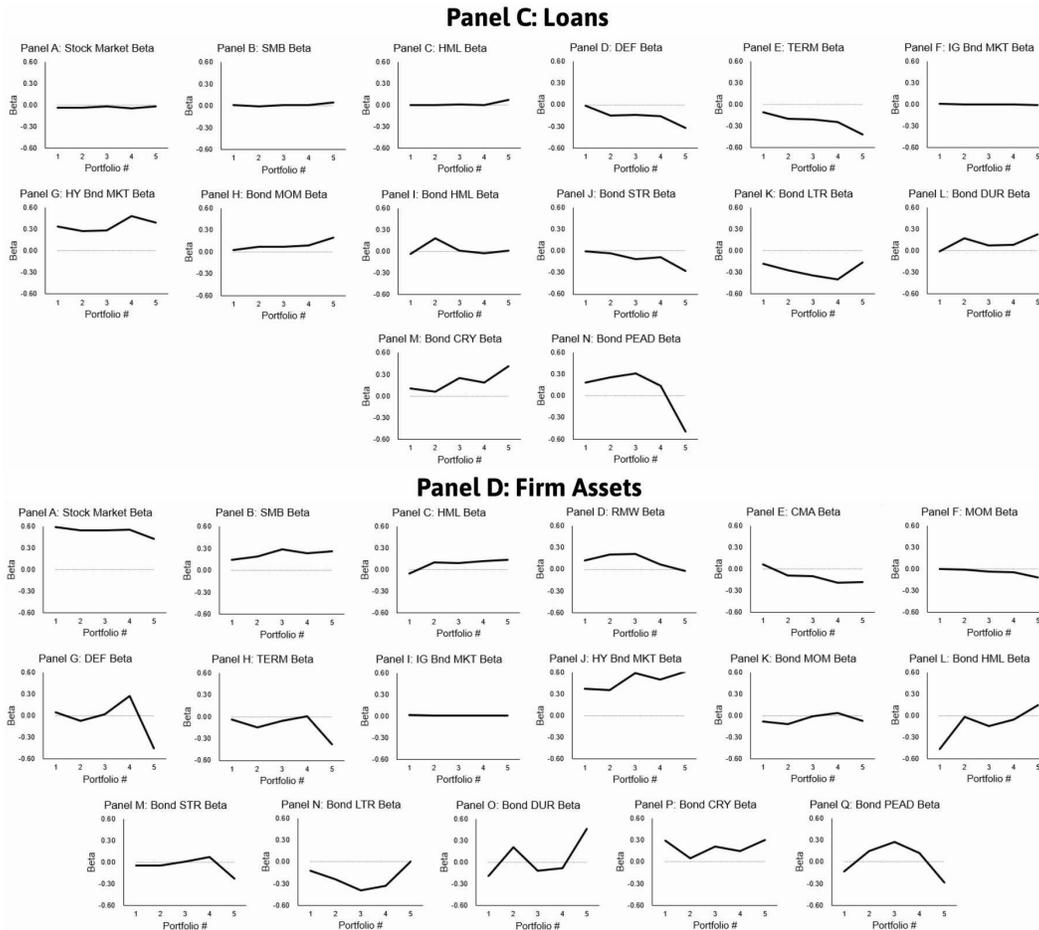


**Figure IA.4: Factor Betas of the Stock-Bond-Loan-Asset Portfolios**

generally produces stock and bond distress-characteristic relations in agreement with those produced by the stock-bond sample. In particular, highly distressed stocks again tend to be small, unprofitable value stocks with a high market beta. Interestingly, however, they now also tend to be loser stocks with an asset growth similar to other stocks. Conversely, highly distressed bonds again tend to be (slightly) smaller, short-maturity-time, and high-coupon-rate bonds with low credit ratings. Also as before, they tend to have a high value-at-risk, a low one-month-lagged past return, a high liquidity beta, and a high illiquidity. Noteworthy, however, they now also have markedly higher bond market betas but an aggregate bond market capitalization indistinguishable from other bonds.

The loan characteristics in Panel C show that while the value-weighted average loan capitalization forms a pronounced inverted U-shape over the distress portfolios, the aggregate loan capitalization is far more flat over them. Analogous to the bond portfolio characteristics in Panel B, highly distressed loans also tend to have a short maturity time. Finally, the firm-asset characteristics in Panel D suggest that the aggregate firm-asset capitalization strongly drops over the portfolios.

In Figure IA.4, we assess the full-sample beta loadings of the same stock (Panel A), bond (Panel B),



**Figure IA.4: Factor Betas of the Stock-Bond-Loan-Asset Portfolios (continued)**

The figure shows the full-sample betas of the stock (Panel A), firm-specific bond (Panel B), firm-specific loan (Panel C), and firm-specific asset (Panel D) portfolios univariately sorted on distress risk on the FF6S, SB14, SB14, and SB17 factor-model factors, respectively. See Appendix A at the end of the main paper for more details about the construction of the factors included in the FF6S, SB14, and SB17 factor models.

loan (Panel C), and firm-asset (Panel D) distress portfolios on the FF6S, SB14, SB14, and SB17 model factors, respectively. Panels A and B confirm that the stock and bond portfolios attract similar beta relations across the stock-bond and the stock-bond-loan-asset samples. Noteworthy exceptions for the stock portfolios are that the RMW beta is now, surprisingly, more inverted U-shaped (rather than declining) over the portfolios, while the MOM beta is now more declining (rather than flat) over them. Conversely, a noteworthy exception for the bond portfolios is that the TERM beta is

more flat (rather than declining) over the portfolios. In agreement with the insight that both bonds and loans constitute debt, Panel C reveals that the loan portfolios often produce similar distress-beta relations as the bond portfolios in Panel B. Different from the bond portfolios, the DEF and TERM betas, however, markedly drop over the loan portfolios, while the duration and carry betas rise over them. Finally, Panel D indicates that the DEF and TERM betas drop over the firm-asset portfolios, while the high-yield bond market, bond HML, and bond duration betas all rise over them.

Using a design and methodology identical to Internet Appendix Table [IA.5](#), Internet Appendix Table [IA.8](#) tabulates the mean returns of the high-minus-low stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) distress spread portfolios in the stock-bond-loan-asset sample separately for each of the twelve months after portfolio formation. Panels A and B suggest that, in contrast to the stock-bond sample, the stock distress premium stays significant for only about 2-3 months after portfolio formation and the bond distress premium for about 1-4 months in that sample. In comparison, the loan distress premium in Panel C continues to be significant for about 3-6 months after portfolio formation and the firm-asset distress premium in Panel D for about 2-3 months. Surprisingly, the equally-weighted portfolios and FM regressions now yield distress premiums staying significant for less long than the value-weighted portfolios. As always, the standard and BGN bond and loan returns produce close-to-identical results. As we discuss in greater detail in our main paper, the weaker persistence of the distress premiums in the stock-bond-loan-asset sample is plausibly driven by that sample being tilted toward larger firms (as they are more likely to own traded loans), and the evidence that larger firms produce weaker asset pricing anomalies (see [Fama and French \(2008\)](#)).

## **IA.5 Robustness Tests on the Pricing of Distress Risk**

In this section, we run several robustness tests on the pricing of corporate distress risk in stocks, bonds, loans, and firm assets. We first assess the effects of matrix prices on our conclusions. We then look into whether controlling for illiquidity and/or liquidity risk alters those conclusions. We next evaluate the effects of unidentified changes in bond and loan ownership spurred by M&A deals. We finally

scrutinize how well our stock, bond, and loan replication strategy in Equation (3) in our main paper is able to capture true (unlevered) asset returns, paying particular attention to the underweighting of loans in that strategy and the omission of non-traded liabilities, such as trade credit.

### IA.5.1. The Effects of Matrix Prices

We start off with looking into the concern that our stock-bond and stock-bond-loan-asset samples contain bond returns calculated from matrix prices because a subset of the Lehman Brothers and Datastream and all of the ICE prices are such prices. Yet, since matrix prices are often stale and/or of a notoriously poor quality, their inclusion in our empirical work may distort our results. To verify that our results are robust, we repeat all portfolio sorts and FM regressions on the pricing of distress risk based on data exclusively featuring bond returns calculated from transaction prices. As TRACE is the only bond price database featuring a comprehensive set of bond transaction prices (recall that NAIC covers only the transaction prices of trades made by insurance firms), we can run this robustness test only on the TRACE sample period from July 2002 to December 2020.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables IA.9 to IA.12 present our results from the portfolio sorts and the FM regressions on distress risk in the stock-bond and stock-bond-loan-asset sample including only bond returns calculated from TRACE transaction prices. The tables confirm that omitting matrix prices and focusing on a more recent sample period do not materially alter our conclusions. Specifically, mean bond, loan, and asset returns continue to decline significantly with distress risk in all but one single regression (see the loans-with-stocks regression in column (7) of Table IA.12). For example, the monthly standard-return SB14 alpha drops by 0.53% ( $t$ -statistic:  $-5.80$ ) over the value-weighted bond deciles in the stock-bond sample (see column (1) in Panel A of Table IA.9). The same alpha drops by 0.26% ( $t$ -statistic:  $-2.10$ ) over the value-weighted loan quintiles in the stock-bond-loan-asset sample (see column (1) in Panel C.1 in Table IA.11). Finally, while *LowDistress* yields an insignificant monthly premium of 0.14% in the FM regression explaining standard firm-asset returns in the stock-bond-loan-asset sample, the corresponding number for *HighDistress* is  $-0.87\%$  ( $t$ -statistic:  $-4.18$ ; see column (8) of Table IA.12).

### IA.5.2. The Effects of Illiquidity and Liquidity Risk

We next address the concern that we do not control for bond illiquidity and liquidity risk in our main tests. This concern is particularly valid as distress risk is positively related to the proxies for these factors advocated in [Bao et al. \(2011\)](#) and [Lin et al. \(2011\)](#); recall Internet Appendix Tables [IA.4](#) and [IA.7](#)), and the same authors find that mean bond returns rise with both proxies. The reason that we do not control for the proxies in our main tests is that we require daily bond-price data to calculate them, and that only the TRACE database contains such data over the shorter sample period from July 2002 to December 2020. Notwithstanding, we next verify that our results are not driven by illiquidity and liquidity risk by repeating our portfolio sorts and FM regressions on the pricing of distress risk controlling for the two proxies over the shorter sample period.

We follow [Bao et al. \(2011\)](#) and [Lin et al. \(2011\)](#) in computing their bond illiquidity and liquidity risk proxies, respectively. More specifically, the bond illiquidity proxy is a bond’s daily-price-change autocovariance over the prior month. Conversely, we calculate the liquidity risk proxy by first running bond-specific regressions of the one-day-ahead excess bond return on its contemporaneous counterpart and signed daily trading volume over the prior month and interpret the coefficient on the volume variable as a proxy for the bond’s illiquidity. We then form the monthly change in the cross-sectional average of that coefficient and orthogonalize it with respect to its one-month lagged value and the one-month lagged (scaled) cross-sectional average. We finally run bond-specific regressions of the monthly excess return on the [Fama and French \(1993\)](#) five-factor-model factors (i.e., MKT, SMB, HML, DEF, and TERM) and the orthogonalized change in the cross-sectional average over the prior five years of data, using the coefficient on the orthogonalized change as the liquidity beta.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables [IA.9](#) to [IA.12](#) offer our results from the portfolio sorts and the FM regressions on distress risk in the stock-bond and stock-bond-loan-asset sample controlling for illiquidity and liquidity risk. While the portfolio sorts control for liquidity risk by adding the return on a spread portfolio based on [Pástor and Stambaugh’s \(2003\)](#) stock or [Bao et al. \(2011\)](#) bond illiquidity proxy to the most comprehensive factor model for an asset class, the FM regressions directly add [Bao et al.’s \(2011\)](#) and [Lin et al.’s](#)

(2011) proxies as controls. The tables confirm that controlling for illiquidity and/or liquidity risk does not materially alter our conclusions. Specifically, mean stock, bond, loan, and asset returns continue to decline significantly with distress risk in all but the stock sorts in the stock-bond-loan-asset sample (see Panel A in Table IA.11). For example, the monthly standard-return SB15 alpha drops by 0.52% ( $t$ -statistic:  $-5.69$ ) over the value-weighted bond deciles in the stock-bond sample (see column (2) in Panel A of Table IA.9). The same alpha drops by 0.28% ( $t$ -statistic:  $-2.23$ ) over the value-weighted loan quintiles in the stock-bond-loan-asset sample (see column (2) in Panel C.1 in Table IA.11). Interestingly, while the liquidity proxies are, in line with the literature, often positively related to bond returns in the FM regressions, they never attract statistical significance, presumably due to the comprehensive set of other controls used in our bond regressions.

### IA.5.3. The Effects of M&A-Induced Bond and Loan Ownership Changes

We now examine the effects of unidentified changes in bond and/or loan ownership triggered by M&As on our conclusions about the pricing of distress risk. We use Christian Stolborg’s pre-TRACE and WRDS’s CRSP-TRACE link files to match our bond and firm data and Michael Roberts’s Dealscan-Compustat link file to match our loan and firm data. Using Christian Stolborg’s and WRDS’s link files is problematic since the files use the ticker as main firm identifier and, as tickers can be asynchronously updated in the bond and firm data, keep only the link with the longest duration, inducing them to miss out on changes in bond ownership after M&As.<sup>8</sup> Conversely, using Michael Roberts’s link file is problematic since it matches loans and firms only on the loan origination date.

We rely on the insight from several M&A practitioner books, such as Hooke (2014), that acquiring firms either pay off or assume the (private and public) debt of the target to correctly identify changes in bond and loan ownership after M&As. To be more specific, we follow Choi (2013) and Choi and

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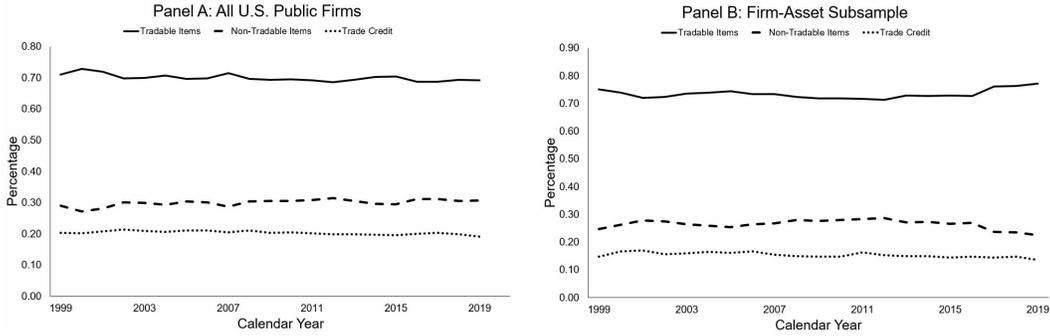
<sup>8</sup>Consider the following example. The company with ticker ABC issued bonds with CUSIP XXX and maturity year 2020 in 2008. In 2018, the company with ticker DEF takes over the company with ticker ABC (so that the company with ticker ABC ceases to exist) and assumes the bonds with CUSIP XXX. As both the bond and firm databases timely update the company ticker, the bond issue will be correctly matched with its original owner over the 2008-2017 period and its new owner over the 2018-2020 period. Yet, as the link files only keep the bond-firm match with the longest duration, they keep only the match over the 2008-2017 but not the one over the 2018-2020 period, to address concern that the latter link is spurious. We thank the WRDS support team for explaining that issue to us.

Richardson (2016) in using the CRSP event file to determine all M&A deals and their corresponding dates in which our sample firms were involved, excluding those after which the acquiror does not fully own the target (as, e.g., acquisitions of assets). We next check whether the outstanding bonds and traded loans of the target continue to be traded for at least one year after the M&A deal. If they are, we posit that the acquiror has assumed those bonds and loans and reassign them to the acquiror on the M&A date. Doing so, we identify about 2,900 single bonds in the stock-bond sample which continue to be traded after an M&A, but no more than 13 traded loans in the stock-bond-loan-asset sample. Manually verifying 20 bonds, our strategy can consistently correctly identify the owner of the bonds.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables IA.13 to IA.16 offer our results from the portfolio sorts and the FM regressions on distress risk in the stock-bond and stock-bond-loan-asset sample using bond and loan data accounting for changes in ownership spurred by M&As. The tables demonstrate that accounting for such changes does not materially alter our conclusions, with mean bond, loan, and firm-asset returns still decreasing with distress risk. For example, the monthly standard-return SB14 alpha drops by 0.47% ( $t$ -statistic:  $-7.66$ ) over the value-weighted bond deciles in the stock-bond sample (see column (1) in Table IA.13). The same alpha drops by 0.37% ( $t$ -statistic:  $-3.05$ ) over the value-weighted loan quintiles in the stock-bond-loan-asset sample (see column (2) in Panel A in Table IA.15). Finally, while *LowDistress* yields an insignificant monthly premium of 0.03% in the FM regression explaining standard firm-asset returns in the stock-bond-loan-asset sample, the corresponding number for *HighDistress* is a much more significant  $-0.76\%$  ( $t$ -statistic:  $-2.98$ ; see column (5) of Table IA.16).

#### IA.5.4. The Effects of Omitted and/or Underweighted Asset Classes

We finally consider the effects of inaccuracies in our asset returns calculated from Equation (3) in our main paper on our conclusions about the pricing of distress risk. There are two obvious sources for such inaccuracies. First, the equation omits possibly important non-traded liabilities, such as trade credit, income taxes payable, and non-controlling interests, as well as traded equities not covered by standard databases, such as preferred stock. Second, the equation underweights loans



**Figure IA.5: The Proportion of Tradable Equity and Liability Claims**

The figure plots the proportions of tradable (solid line) and non-tradable (broken line) equity and liability claims and trade credit (dotted line) for all Compustat (Panel A) and our stock-bond-loan-asset sample (Panel B) firms over the stock-bond-loan-asset sample period (1999-2020). The tradable claims include debt in current liabilities, long-term debt, and common equity. The non-tradable include accounts payable, income taxes payable, current other liabilities, deferred taxes and investment tax credits, noncontrolling other long-term liabilities, long-term other liabilities, and preferred equity. We include preferred equity among the non-tradable claims since it is not covered in standard data sources (as, e.g., CRSP). Trade credit is accounts payable plus 60% of short-term other liabilities.

since, even for firms with traded loans, those only make up some fraction of all their loans.

We rely on Compustat and Capital IQ data to find out whether our asset return calculations omit important non-traded and/or non-covered equities and liabilities. Starting with the Compustat data, Table IA.17 gives the mean proportions of short-term liabilities (first subpanel), long-term liabilities (second), and equities (third) for the entire Compustat universe (Panel A) and the stock-bond-loan-asset subsample (Panel B) over the 1999-2020 sample period. We first calculate the means by fiscal year and then average over time. The short-term liabilities are accounts payable, debt in current liabilities, income taxes payable, and other such liabilities. We add accrued expenses, a component of other short-term liabilities. The long-term liabilities are long-term debt, deferred taxes and investment tax credits, noncontrolling interests, and other such liabilities. We add capitalized leases, a component of long-term debt. The equities are common and preferred equity.

Assuming that debt in current liabilities, long-term debt, and common equity are all tradable and covered by standard databases, the table suggests that our asset return calculations capture between 70-75% of the average firm's financing sources. Strikingly, income taxes payable, capitalized

leases, deferred taxes plus investment tax credits, and non-controlling interests make up an only small proportion of liabilities for the vast majority of firms, with even their 95th percentiles never exceeding 8%. We reach the same conclusion in case of preferred equity, which, although tradable, is not included in CRSP. Conversely, the single important non-traded liability is trade credit, calculated as accounts payable plus accrued expenses<sup>9</sup> and making up between 12-15% of the book value of the average firm’s financing sources. Plotting the cross-sectional mean proportions of traded-and-covered sources, non-traded-and/or-non-covered sources, and trade credit over the 1999-2020 sample period, Figure IA.5 corroborates that these proportions are extremely stable over time.

Switching to the Capital IQ data to learn more about the liability structure of our sample firms, Table IA.18 presents the mean proportions of commercial paper, revolving credit lines, term loans, senior bonds, subordinated bonds, capital leases, trust preferred funds, other borrowing, and the residual adjustment<sup>10</sup> for the entire Capital IQ universe (Panel A) and our stock-bond-loan-asset subsample (Panel B) over the 1999-2020 sample period. Assuming that revolving credit lines, term loans, and senior and subordinated bonds are tradable, the table insinuates that our asset return calculations capture between 83% (full sample) and 93% (stock-bond-loan-asset subsample) of the average firm’s book value of liabilities. In other words, non-traded liabilities such as commercial paper, capital leases, trust preferred funds, general other borrowing, and the residual adjustment make up an only negligible proportion of total liabilities for the vast majority of firms. Interestingly, however, the table also reveals that the book value of loans (revolving credit lines plus term loans) tends to be higher than the book value of bonds (senior plus subordinated bonds) in the stock-bond-loan-asset subsample, directly underlining the concern that loans are underweighted in our asset return calculations (compare with Panels C and D in Figure 1 in our main paper).

We finally present evidence suggesting that the omission of trade credit from and/or the underweighting of loans in our asset return calculations do not distort our conclusions about the pricing

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<sup>9</sup>While accounts payable are trade-debt expenses for which a company has already received an invoice, accrued expenses are those for which it has not yet received an invoice but will do so in the future.

<sup>10</sup>As firms are not obliged to report information on the stated debt instruments, the sum of their outstanding balances is not always equal to the total-debt outstanding balance. To account for that discrepancy, Capital IQ uses the residual adjustment term. Notwithstanding, that term is small for the vast majority of firms.

of distress risk. To do so, we exploit arguments in [Erens and Hoffmann \(2013\)](#) and [Costello \(2019\)](#) implying that trade credit must be close to risk-free. [Erens and Hoffmann \(2013\)](#) reason that since a firm’s relations with its suppliers are essential for its operations, and since it is usually initially attempted to restructure failed firms in the U.S., the managers of failed U.S. firms (and even the bankruptcy trustees) almost always pay trade creditors. Similarly, [Costello \(2019\)](#) explains that, prior to 2005, U.S. suppliers could claim back goods from a failed firm under Article 2-702 of the Universal Commercial Code if a request is filed within ten days. More crucially, she highlights that the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 significantly improved U.S. suppliers’ bargaining position, giving them 45 days to file a claim, allowing them to reclaim the cash value (and not necessarily the sold goods), and awarding them “super-priority rights” (trumping all other claimants including, for example, secured creditors) in bankruptcy proceedings.

Relying on [Erens and Hoffmann’s \(2013\)](#) and [Costello’s \(2019\)](#) arguments, we create pseudo-market values and returns for trade credit. We first retrieve the nominal balances of a firm’s accounts payable and other short-term liabilities from Compustat Quarterly. We then assume a four-month reporting gap and set the trade credit balance to the most recently available sum of the accounts payable and 60% of the other short-term liabilities balances.<sup>11</sup> We subsequently calculate the pseudo-market value of trade credit as its outstanding balance discounted at the current risk-free rate over the average duration of trade credit in [Costello \(2019\)](#), which is about one month. Conversely, we set the return on trade credit equal to the risk-free rate over the next month. Using the pseudo-market values and returns, we calculate alternative asset returns including trade credit,  $r^{A(1)}$ , from:

$$r_{i,t}^{A(1)} = \left( \frac{E_{i,t-1}}{MV_{i,t-1}^{(1)}} \right) r_{i,t}^S + \left( \frac{B_{i,t-1}}{MV_{i,t-1}^{(1)}} \right) r_{i,t}^{BP} + \left( \frac{L_{i,t-1}}{MV_{i,t-1}^{(1)}} \right) r_{i,t}^{LP} + \left( \frac{TC_{i,t-1}}{MV_{i,t-1}^{(1)}} \right) r_{i,t}^{TC}, \quad (\text{IA.1})$$

where  $MV^{(1)}$  is the sum of the market values of stocks, bonds, loans, and trade credit,  $E + B + L + TC$ ,  $TC$  is the pseudo-market value of trade credit, and  $r^{TC}$  is the return on trade credit.

We also take steps toward correcting the downward bias inherent in the loan weights in our asset

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<sup>11</sup>We approximate accrued expenses as 60% of other short-term liabilities as many firms do not report those expenses.

return calculations. In particular, we first retrieve data on the outstanding balances of revolving credit lines, term loans, senior bonds, and subordinated bonds from Capital IQ. As before, we assume a four-month reporting gap and then set the bond (loan) balance to the sum of the senior and subordinated bond (revolving credit line and term loan) balances. Assuming that the loan-to-bond outstanding-balance ratio is similar to the corresponding market-value ratio, we next multiply the market value of bonds,  $B$ , with the outstanding-balance ratio, to infer the implied market value of loans,  $L^{(2)}$ . We finally create alternative asset returns with adjusted loan weights,  $r^{A(2)}$ , from:

$$r_{i,t}^{A(2)} = \left( \frac{E_{i,t-1}}{MV_{i,t-1}^{(2)}} \right) r_{i,t}^S + \left( \frac{B_{i,t-1}}{MV_{i,t-1}^{(2)}} \right) r_{i,t}^{BP} + \left( \frac{L_{i,t-1}^{(2)}}{MV_{i,t-1}^{(2)}} \right) r_{i,t}^{LP}, \quad (\text{IA.2})$$

where  $MV^{(2)}$  is the sum of the stock, bond, and implied loan values,  $E + B + L^{(2)}$ .

A downside of the above loan-weight-adjustment strategy is that it requires the existence of bonds in a firm's capital structure to be feasible. As, however, illustrated in Panel C of Figure 1 of our main paper, not all firms with traded loans also own bonds. To address that issue, we also rely on an alternative strategy. In particular, we use Mergent FISD to calculate the aggregate balance of all outstanding bonds of a firm at the end of month  $t$ . We next subtract that balance from the firm's book value of short plus long-term debt from Compustat to approximate the aggregate balance of all its outstanding loans at that time. Using the firm's book value of equity, its outstanding bond balance, and its outstanding loan balance, we then calculate its stock, bond, and loan weights. We finally calculate its asset return based on those weights,  $r^{A(3)}$ , from:

$$r_{i,t}^{A(3)} = \left( \frac{E_{i,t-1}^{(3)}}{MV_{i,t-1}^{(3)}} \right) r_{i,t}^S + \left( \frac{B_{i,t-1}^{(3)}}{MV_{i,t-1}^{(3)}} \right) r_{i,t}^{BP} + \left( \frac{L_{i,t-1}^{(3)}}{MV_{i,t-1}^{(3)}} \right) r_{i,t}^{LP}, \quad (\text{IA.3})$$

where  $E^{(3)}$  is book equity,  $B^{(3)}$  the outstanding bond balance,  $L^{(3)}$  the outstanding loan balance, and  $MV^{(3)} = E^{(3)} + B^{(3)} + L^{(3)}$ . While Equation (IA.3) can be applied to firms with and without bonds, it relies on book (and not market) values to calculate the asset weights.<sup>12</sup>

<sup>12</sup>In untabulated tests, we also looked into combinations of the trade-credit adjustment and each of the loan-weight adjustments, finding that these combinations yield results in agreement with the single adjustments.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables [IA.19](#) to [IA.20](#) present our results from firm-asset portfolio sorts and FM regressions using the original, trade-credit-adjusted, and loan-weight-adjusted asset returns. The tables suggest that the adjustments do not alter our conclusion that mean firm-asset returns are either hump-shaped in or decline with distress risk. Looking into Panel A of Table [IA.19](#), the original SB17 alpha declines by 0.66% ( $t$ -statistic:  $-2.71$ ) over the value-weighted standard-return portfolios. In contrast, the trade-credit-adjusted SB17 alpha declines by 0.54% ( $t$ -statistics:  $-2.63$ ) over those same portfolios, while the loan-weight-adjusted alphas decline by 0.63% and 0.56% ( $t$ -statistics:  $-2.76$  and  $-2.71$ ), respectively. Overall, the changes in the SB17 alpha over the portfolios and their corresponding inference levels are always highly similar across all alternative asset return specifications.

## IA.6 Shareholder Advantage and the Distress Anomaly

While [Garlappi et al. \(2008\)](#) and [Garlappi and Yan \(2011\)](#) propose an alternative explanation for the negative stock distress premium grounded in shareholders' ability to extract rents from debtholders in distress ("shareholder advantage theory"), [Avramov et al. \(2022\)](#) argue that the negative debt distress premiums estimated in their work and ours cast a serious blow to that explanation. To formalize that claim, we use [Fan and Sundaresan's \(2000\)](#) real options model of a stock-and-debt financed firm in which shareholders can strategically default to show that while a higher shareholder advantage does indeed yield a *less* positive stock distress premium, it is unable to produce a negative debt distress premium. We start off with outlining the model's assumptions. We next give the model's closed-form solutions for distress risk and the expected asset, stock, and debt return. We finally follow [Garlappi et al. \(2008\)](#) in using simulations to evaluate how shareholder advantage conditions the relations between distress risk and the expected asset, stock, or debt return in the model.

### IA.6.1. Fan and Sundaresan's (2000) Modelling Assumptions

Let us consider a stock-and-debt financed firm operating over a continuous infinite time horizon indexed by  $t \in [0, \infty)$  and exposed to corporate taxes and deadweight costs of bankruptcy. The firm's unlevered value,  $V_t$ , obeys the geometric Brownian motion (GBM):

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dB_t, \quad (\text{IA.4})$$

where  $\mu$  is the expected return of the unlevered assets,  $\delta < \mu$  the dividend yield,  $\sigma$  the volatility of the unlevered assets, and  $dB_t$  the increment of a standard Brownian motion. In each instant, the firm is taxed at a constant rate of  $\tau$ , creating a tax shield of debt. Upon defaulting, the firm loses the fraction  $\alpha$  of its value in direct and/or indirect bankruptcy costs.

The firm is financed through both equity and debt. The debt comes in the form of a perpetuity requiring an instantaneous payment of  $c$  per time unit. Importantly, shareholders have the (perpetual) option to strategically default on that debt payment, triggering a renegotiation between them and debtholders about the residual firm value. The outcome of that renegotiation are the fractions of residual firm value awarded to shareholders ( $\tilde{\theta}$ ) and debtholders ( $1 - \tilde{\theta}$ ), which are determined through a Nash bargaining game. More specifically, the fraction awarded to shareholders,  $\tilde{\theta}$ , maximizes the joint benefit to shareholders and debtholders and can be written as:

$$\tilde{\theta} = \operatorname{argmax} \left[ \tilde{\theta} v(V) - 0 \right]^\eta \left[ (1 - \tilde{\theta}) v(V) - (1 - \alpha)V \right]^{(1-\eta)} = \eta \left( 1 - \frac{(1 - \alpha)V}{v(V)} \right), \quad (\text{IA.5})$$

where  $v(V)$  is the firm's levered asset value and  $\eta$  shareholders' bargaining power. Equation (IA.5) demonstrates that, in line with intuition, the fraction of firm value awarded to shareholders rises with shareholders' bargaining power,  $\eta$ , and the deadweight costs of bankruptcy,  $\alpha$ .

### IA.6.2. Model Solutions

In this setup, [Fan and Sundaresan \(2000\)](#) show that the value of the levered assets,  $v(V)$ , is:

$$v(V) = \begin{cases} V + \frac{\tau c}{r} - \frac{\lambda_2}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} & \text{if } V > \tilde{V}_S, \\ V + \frac{-\lambda_1}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V}{\tilde{V}_S}\right)^{\lambda_2} & \text{if } V \leq \tilde{V}_S, \end{cases} \quad (\text{IA.6})$$

where  $\tilde{V}_S$ , the constant unlevered-asset-value threshold at or below which shareholders optimally strategically default on repaying the outstanding debt, is equal to:

$$\tilde{V}_S = \frac{c(1 - \tau + \eta\tau)}{r} \frac{-\lambda_1}{1 - \lambda_1} \frac{1}{1 - \eta\alpha}, \quad (\text{IA.7})$$

and:

$$\lambda_1 = \left(\frac{1}{2} - \frac{r - \delta}{\sigma^2}\right) - \sqrt{\left(\frac{1}{2} - \frac{r - \delta}{\sigma^2}\right)^2 + \frac{2r}{\sigma^2}} < 0, \quad (\text{IA.8})$$

$$\lambda_2 = \left(\frac{1}{2} - \frac{r - \delta}{\sigma^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{r - \delta}{\sigma^2}\right)^2 + \frac{2r}{\sigma^2}} > 1. \quad (\text{IA.9})$$

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

$$\tilde{E}(V) = \begin{cases} V - \frac{c(1-\tau)}{r} + \left[ \frac{c(1-\tau)}{(1-\lambda_1)r} - \frac{\lambda_1(1-\lambda_2)\eta}{(\lambda_2-\lambda_1)(1-\lambda_1)} \frac{\tau c}{r} \right] \left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} & \text{if } V > \tilde{V}_S, \\ \theta^* v(V) & \text{if } V \leq \tilde{V}_S, \end{cases} \quad (\text{IA.10})$$

and that the value of debt,  $\tilde{D}(V)$ , is the levered asset value minus the equity value,  $v(V) - \tilde{E}(V)$ .

In turn, [Garlappi et al. \(2008\)](#) establish that the time-0 probability that shareholders strategically default over the period until time  $T$ ,  $\text{Prob}_{(0,T]}(V_0)$ , is:

$$\text{Pr}_{(0,T]} = N\left(\frac{\ln(\tilde{V}_S) - \ln(V_0) - \gamma T}{\sigma\sqrt{T}}\right) + e^{\frac{2\gamma(\ln(\tilde{V}_S) - \ln(V_0))}{\sigma^2}} N\left(\frac{\ln(\tilde{V}_S) - \ln(V_0) + \gamma T}{\sigma\sqrt{T}}\right), \quad (\text{IA.11})$$

where  $\gamma = \mu - \delta - \frac{1}{2}\sigma^2$ , and  $N(\cdot)$  is the cumulative standard normal distribution. To calculate the

expected stock return over the period until time  $t$ ,  $\mathbb{E}_0(\tilde{E}(V_t))/\tilde{E}(V_0)$ , they next show that:

$$\begin{aligned}
\mathbb{E}_0(\tilde{E}(V_t)) &= \eta\alpha V_0 e^{(\mu-\delta)t} N(h(t) - \sigma\sqrt{t}) \\
&- \eta \frac{\lambda_1}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_2} e^{\lambda_2(\gamma-\lambda_2)t} N(h(t) - \lambda_2\sigma\sqrt{t}) \\
&+ V_0 e^{(\mu-\delta)t} N(-h(t) + \sigma\sqrt{t}) - \frac{c(1-\tau)}{r} N(-h(t)) \\
&+ \left[ \frac{c(1-\tau)}{(1-\lambda_1)r} - \frac{\lambda_1(1-\lambda_2)\eta}{(\lambda_2-\lambda_1)(1-\lambda_1)} \frac{\tau c}{r} \right] \left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} \\
&\times e^{\lambda_1(\gamma-\lambda_1)t} N(-h(t) + \lambda_1\sigma\sqrt{t}), \tag{IA.12}
\end{aligned}$$

where  $h(t) = \frac{\ln(\tilde{V}_S/V_0) - \gamma t}{\sigma\sqrt{t}}$ , and then scale that with the equity value in Equation (IA.10),  $\tilde{E}(V_0)$ .

We finally use techniques analogous to [Garlappi et al. \(2008\)](#) to also derive the expected debt return over the period until time  $t$ ,  $\mathbb{E}_0(\tilde{D}(V_t))/\tilde{D}(V_0)$ . To do so, we first recall that the value of debt is the value of the levered assets minus the equity value (i.e.,  $\tilde{D}(V) = v(V) - \tilde{E}(V)$ ). We can thus calculate  $\mathbb{E}_0(\tilde{D}(V_t))$  from the time-0 expectation of the levered asset value at time  $t$ ,  $\mathbb{E}_0(v(V_t))$ . To form the levered-asset-value expectation, we write the unlevered asset value at time  $t$  as:

$$V_t = V_0 e^{(\mu - \delta - \frac{1}{2}\sigma^2)t + \sigma(B_t - B_0)}, \tag{IA.13}$$

which is log-normally distributed with  $E[\ln V_t] = \ln V_0 + \gamma t$  and  $\text{Var}[\ln V_t] = \sigma^2 t$ . We next 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 the equality:

$$\int_0^a V_t^b p(V_t) dV_t = \int_0^a V_t^b \frac{1}{\sqrt{2\pi\sigma^2 t} V_t} e^{-\frac{1}{2} \left( \frac{\ln V_t - (\ln V_0 + \gamma t)}{\sigma\sqrt{t}} \right)^2} dV_t. \tag{IA.14}$$

Using the change of variable  $X_t = \frac{\ln V_t - \ln V_0 - \gamma t}{\sigma\sqrt{t}}$ , the right-hand side of Equation (IA.14) becomes:

$$\int_{-\infty}^{\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}}} e^{b(\ln V_0 + \gamma t + \sigma\sqrt{t}X_t)} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}X_t^2} dX_t \quad (\text{IA.15})$$

$$= V_0^b e^{b\gamma t} \int_{-\infty}^{\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}X_t^2 + b\sigma\sqrt{t}X_t - \frac{1}{2}b^2\sigma^2 t + \frac{1}{2}b^2\sigma^2 t} dX_t \quad (\text{IA.16})$$

$$= V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(X_t - 2b\sigma\sqrt{t})^2 + b^2\sigma^2 t} dX_t \quad (\text{IA.17})$$

$$= V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(X_t - b\sigma\sqrt{t})^2} dX_t. \quad (\text{IA.18})$$

Using the change of variable  $Y_t = X_t - b\sigma\sqrt{t}$ , we can write expression (IA.18) as:

$$V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0) - \gamma t - b\sigma\sqrt{t}}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}Y_t^2} dY_t \quad (\text{IA.19})$$

$$= V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} N\left(\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}} - b\sigma\sqrt{t}\right). \quad (\text{IA.20})$$

Relying on identical techniques, we can also show that:

$$\int_a^\infty V_t^b p(V_t) dV_t = V_0^b e^{b\gamma t + \frac{1}{2}b^2\sigma^2 t} N\left(-\frac{\ln(a/V_0) - \gamma t}{\sigma\sqrt{t}} + b\sigma\sqrt{t}\right). \quad (\text{IA.21})$$

Using Equation (IA.6), we next write the expected levered asset value at time  $t$ ,  $\mathbb{E}_0(v(V_t))$ , as:

$$\begin{aligned} \mathbb{E}_0(v(V_t)) &= \int_0^\infty V_t p(V_t) dV_t + \int_{\tilde{V}_S}^\infty \frac{\tau c}{r} p(V_t) dV_t - \int_{\tilde{V}_S}^\infty \frac{\lambda_2}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V_t}{\tilde{V}_S}\right)^{\lambda_1} p(V_t) dV_t \\ &+ \int_0^{\tilde{V}_S} \frac{-\lambda_1}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V_t}{\tilde{V}_S}\right)^{\lambda_2} p(V_t) dV_t \\ &= \int_0^\infty V_t p(V_t) dV_t + \frac{\tau c}{r} \int_{\tilde{V}_S}^\infty p(V_t) dV_t - \frac{\lambda_2}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{1}{\tilde{V}_S}\right)^{\lambda_1} \int_{\tilde{V}_S}^\infty V_t^{\lambda_1} p(V_t) dV_t \\ &+ \frac{-\lambda_1}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{1}{\tilde{V}_S}\right)^{\lambda_2} \int_0^{\tilde{V}_S} V_t^{\lambda_2} p(V_t) dV_t. \end{aligned} \quad (\text{IA.22})$$

Exploiting the closed-form solutions for the integrals  $\int_0^a V_t^b p(V_t) dV_t$  and  $\int_a^\infty V_t^b p(V_t) dV_t$  in Equa-

tions (IA.20) and (IA.21), respectively, we finally write Equation (IA.22) as:

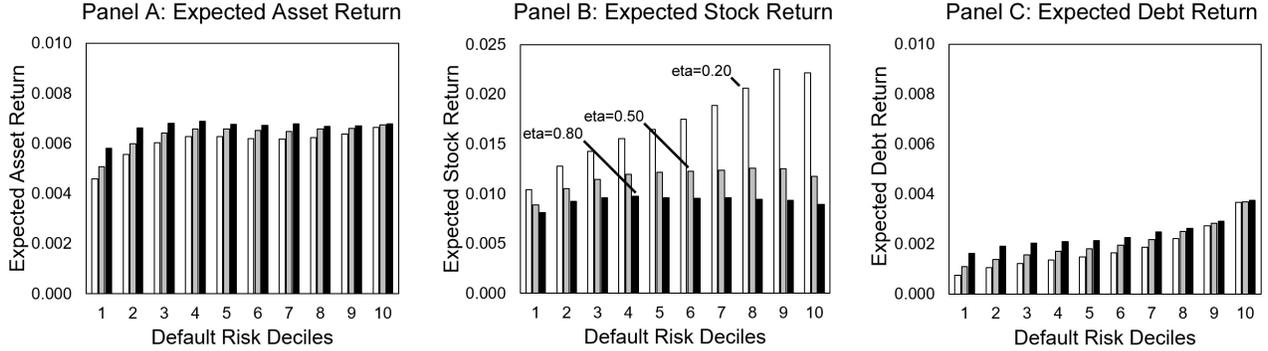
$$\begin{aligned}
\mathbb{E}_0(v(V_t)) &= V_0 e^{(\mu-\delta)t} + \frac{\tau c}{r} N(-h(t)) \\
&- \frac{\lambda_2}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_1} e^{\lambda_1(\gamma + \frac{1}{2}\lambda_1\sigma^2)t} N(-h(t) + \lambda_1\sigma\sqrt{t}) \\
&+ \frac{-\lambda_1}{\lambda_2 - \lambda_1} \frac{\tau c}{r} \left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_2} e^{\lambda_2(\gamma + \frac{1}{2}\lambda_2\sigma^2)t} N(h(t) - \lambda_2\sigma\sqrt{t}). \tag{IA.23}
\end{aligned}$$

Subtracting the time-0 expectation of the equity value in Equation (IA.12) from the time-0 expectation of the levered asset value in Equation (IA.23), we obtain the time-0 expectation of the debt value (i.e.,  $\mathbb{E}_0(\tilde{D}(V_t)) = \mathbb{E}_0(v(V_t)) - \mathbb{E}_0(\tilde{E}(V_t))$ ). Scaling the time-0 debt-value expectation with the current debt value, which is the current levered asset value in Equation (IA.6) minus the current equity value in Equation (IA.10), we obtain the expected debt return from time 0 to  $t$ .

### IA.6.3. Shareholder Advantage and Expected Returns

We finally follow [Garlappi et al. \(2008\)](#) in using simulations to find out how shareholder advantage affects the relations between default risk and expected asset, stock, and debt returns in the model. To that end, we generate a cross-section of 100,000 artificial firms. We calculate each firm's default risk over the period from  $t = 0$  to 1 from Equation (IA.11) and its three expected returns over the period from  $t = 0$  to 1/12 from Equations (IA.6), (IA.10), (IA.12), and (IA.23). Consistent with [Garlappi et al. \(2008\)](#), we set the riskfree rate of return,  $r$ , to 0.04 per annum, the payout rate,  $\delta$ , to 0.04, the tax rate,  $\tau$ , to 0.35, and the bankruptcy cost,  $\alpha$ , to 0.50. Also in line with them, we draw the coupon rate,  $c$ , the expected unlevered asset return,  $\mu$ , 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, unlike them, we do not have access to the asset volatility estimates from Moody's KMV Corporation, we also draw the asset volatility,  $\sigma$ , from a uniform distribution with support  $[0.10, 0.30]$ . We finally set the shareholder bargaining power parameter  $\eta$  to either 0.20, 0.50, or 0.80.

Figure IA.6 displays the monthly expected levered-asset (Panel A), stock (Panel B), and debt (Panel C) returns of equally-weighted decile portfolios containing the 100,000 artificial firms and sorted



**Figure IA.6: Shareholder Advantage and Expected Asset, Stock, and Debt Returns**

The figure offers the expected levered-asset (Panel A), stock (Panel B), and debt (Panel C) returns of equally-weighted default risk portfolios conditional on a shareholder advantage of 0.20 (white bar), 0.50 (grey), and 0.80 (black).

according to one-year default risk. In agreement with [Garlappi et al. \(2008\)](#), Panel B suggests that a greater shareholder advantage (i.e., a higher  $\eta$ ) creates a less positive and more downward hump-shaped default risk-expected stock return relation. The reason is that shareholders own the levered assets net of coupon payments plus a put option to stop paying coupons and to start negotiations about the firm's residual value. As shareholders' bargaining power increases, the value of the put option rises, especially when default risk is high, and, as the systematic risk of the put option is negative, its greater value drags down the expected stock return. In contrast, as debtholders are short that same put option, and the systematic risk of a short put option is positive, Panel C reveals that a higher shareholder bargaining power creates a more positive default risk-expected debt return relation, at least once we control for expected levered-asset return changes coming from the initial unlevered-asset-value draws depending on the strategic default threshold  $V_G$  (see Panel A). Notwithstanding the expected levered-asset return effect, the main lesson to take away from Figure IA.6 is that, independent of shareholders' bargaining power, the default risk-expected debt return relation is always positive. The upshot is that shareholder advantage cannot explain negative distress premiums in debt.

## IA.7 Disinvestment Options and the Distress Anomaly

In Section IV of our main paper, we show that a real options model of a stock-and-debt financed firm with capacity utilization, investment, and disinvestment choices can explain the negative stock and debt distress premiums obtained in our empirical work. In this section of the Internet Appendix, we derive the model's quasi-closed-form solutions for the firm's asset value and its expected asset return. We also offer more details about the Monte Carlo simulations run to derive the firm's equity and debt values and its expected stock and debt returns. We finally give comparative statics for the conclusions about the distress risk-expected return relations derived from the model.

### IA.7.1. Deriving the Asset Value Model Solution

We first derive the model's closed-form solutions for the firm's asset value and its expected asset return. As we stress in our main paper, the firm's asset value is the sum of the values of its incremental options to produce (assets-in-place) and its incremental options to acquire more options to produce (growth options). We use the risk-neutral measure to value all the incremental options. In particular, denoting the value of the incremental option on asset increment  $k$  (either an asset-in-place or growth option) by  $\Delta C(\theta; k)$ , the definition of the risk-neutral measure gives us:

$$E^{\mathbb{Q}} \left[ \frac{d\Delta C(\theta; k) + \pi(\theta; k)dt}{\Delta C(\theta; k)} \right] = rdt, \quad (\text{IA.24})$$

where  $E^{\mathbb{Q}}[\cdot]$  is an expectation under the equivalent martingale measure and  $\pi(\theta; k)$  is the one-time-unit cash flow paid out by the incremental option in the current instant. Intuitively, Equation (IA.24) states that the expected return of any asset under the risk-neutral measure is equal to the risk-free rate of return. Using Itô's lemma, simplifying, and rearranging, we obtain:

$$\frac{1}{2}\sigma^2\theta^2\frac{\partial^2\Delta C(\theta; k)}{\partial\theta^2} + (r - \delta)\theta\frac{\partial\Delta C(\theta; k)}{\partial\theta} - r\Delta C(\theta; k) + \pi(\theta; k) = 0, \quad (\text{IA.25})$$

which the value of the incremental option has to fulfill subject to boundary conditions.

Dealing with the valuation of the assets-in-place first, we need to separately consider the cases in which (i) the firm first switches off an option to produce and then sells it and in which (ii) it sells off the switched-on option to produce. Starting with the first case, the firm optimally switches on the option to produce the  $k$ th output increment when the output price exceeds its variable cost, that is, when  $\theta \geq c_1 + c_2k$  (see Section B in our main paper). In this case, it is well-known that the value of this incremental option,  $\Delta V(\theta; k)$ , is of the general form:

$$\Delta V(\theta; k) = A_O \theta^{\beta_1} + B_O \theta^{\beta_2} + \frac{\theta}{\delta} - \frac{c_1 + c_2k + f}{r}, \quad (\text{IA.26})$$

where  $A_O$  and  $B_O$  are free parameters, and:

$$\beta_1 = \frac{1}{2} - (r - \delta)/\sigma^2 + \sqrt{\left[(r - \delta)/\sigma^2 - \frac{1}{2}\right]^2 + 2r/\sigma^2} > 1, \quad (\text{IA.27})$$

$$\beta_2 = \frac{1}{2} - (r - \delta)/\sigma^2 - \sqrt{\left[(r - \delta)/\sigma^2 - \frac{1}{2}\right]^2 + 2r/\sigma^2} < 0. \quad (\text{IA.28})$$

Since  $\lim_{\theta \rightarrow +\infty} \Delta V(\theta; k)$  is equal to  $\frac{\theta}{\delta} - \frac{c_1 + c_2k + f}{r}$ , we immediately have  $A_O = 0$ . Conversely, when  $\theta^D \leq \theta < c_1 + c_2k$ , where  $\theta^D$  is the disinvestment output-price threshold, the firm optimally switches off the option. In this case, the value of the option is of the general form:

$$\Delta V(\theta; k) = A_I \theta^{\beta_1} + B_I \theta^{\beta_2} - \frac{f}{r}, \quad (\text{IA.29})$$

where  $A_I$  and  $B_I$  are free parameters. Finally, when the output price drops below  $\theta^D$ , that is, when  $\theta \leq \theta^D < c_1 + c_2k$ , the value of the option is equal to the disinvestment proceeds  $S$ .

To find the values of  $A_I$ ,  $B_I$ ,  $B_O$ , and  $\theta^D$ , we ensure that the three component solutions value-

match with and smooth-paste into another. In particular, we require that:

$$B_O(\theta^P)^{\beta_2} + \frac{(\theta^P)}{\delta} - \frac{c_1 + c_2k + f}{r} = A_I(\theta^P)^{\beta_1} + B_I(\theta^P)^{\beta_2} - \frac{f}{r}, \quad (\text{IA.30})$$

$$B_O\beta_2(\theta^P)^{\beta_2-1} + \frac{1}{\delta} = A_I\beta_1(\theta^P)^{\beta_1-1} + B_I\beta_2(\theta^P)^{\beta_2-1}, \quad (\text{IA.31})$$

$$A_I(\theta^D)^{\beta_1} + B_I(\theta^D)^{\beta_2} - \frac{f}{r} = S, \quad (\text{IA.32})$$

$$A_I\beta_1(\theta^D)^{\beta_1-1} + B_I\beta_2(\theta^D)^{\beta_2-1} = 0, \quad (\text{IA.33})$$

where  $\theta^P \equiv c_1 + c_2k$ . Equation (IA.30) ensures that the values of the switched-on and switched-off options are identical at the optimal switching threshold  $\theta^P$ , while Equation (IA.31) ensures that their partial derivatives with respect to the output price are also identical at that point. Conversely, Equation (IA.32) ensures that the value of the switched-off option is equal to the disinvestment proceeds at the disinvestment threshold  $\theta^D$ , while Equation (IA.33) ensures that the partial derivative of that option's value with respect to the output price is equal to zero at that point.

Solving for  $A_I$ ,  $B_O - B_I$ ,  $B_I$ , and  $\theta^D$ , we obtain:

$$A_I = \left( \frac{r - \beta_2(r - \delta)}{r\delta(\beta_1 - \beta_2)} \right) (\theta^P)^{1-\beta_1}, \quad (\text{IA.34})$$

$$B_O - B_I = \left( \frac{r - \beta_1(r - \delta)}{r\delta(\beta_1 - \beta_2)} \right) (\theta^P)^{1-\beta_2}, \quad (\text{IA.35})$$

$$B_I = \frac{S + f/r}{1 - \beta_2/\beta_1} (\theta^D)^{-\beta_2}, \quad (\text{IA.36})$$

$$\theta^D = \left( \left( \frac{1}{A_I} \right) \left( \frac{S + f/r}{1 - \beta_1/\beta_2} \right) \right)^{1/\beta_1}. \quad (\text{IA.37})$$

We use Equation (IA.34) to calculate  $A_I$ . We plug  $A_I$  into Equation (IA.37) to calculate  $\theta^D$ . We next plug  $\theta^D$  into Equation (IA.36) to calculate  $B_I$ . We finally use Equation (IA.35) to calculate  $B_O$ .

Turning to the second case in which the firm optimally sells the switched-on option, the general form of the value of the option is still given by Equation (IA.26) when  $\theta \geq \theta^D$ . Also, its value is still equal to the disinvestment proceeds  $S$  when  $\theta < \theta^D$ . To find the values of  $B_O$  and  $\theta^D$  in this case,

we ensure that the component solutions value-match with and smooth-paste into another:

$$B_O(\theta^D)^{\beta_2} + \frac{(\theta^D)}{\delta} - \frac{c_1 + c_2k + f}{r} = S, \quad (\text{IA.38})$$

$$B_O\beta_2(\theta^D)^{\beta_2-1} + \frac{1}{\delta} = 0, \quad (\text{IA.39})$$

where Equation (IA.38) ensures that the value of the switched-on option is equal to the disinvestment proceeds at the disinvestment threshold, while Equation (IA.39) ensures that its partial derivative with respect to the output price is zero at that point. Solving for  $B_O$  and  $\theta^D$ , we obtain:

$$B_O = -\frac{1}{\delta\beta_2}(\theta^D)^{1-\beta_2}, \quad (\text{IA.40})$$

$$\theta^D = \frac{\delta\beta_2(S + (c_1 + c_2k + f)/r)}{\beta_2 - 1}. \quad (\text{IA.41})$$

We use Equation (IA.41) to calculate  $\theta^D$  and then plug  $\theta^D$  into Equation (IA.40) to obtain  $B_O$ .

In practice, we always start with the first case. If we then notice that the first case gives us a contradiction (i.e., if we find that  $\theta^D > c_1 + c_2k$ ), we move on to the second case.

We next value the firm's growth options. Recalling the well-known insight that a perpetual call option whose value depends only on some stochastic variable is optimally exercised once the stochastic variable hits some threshold from below, we can write the pre-exercise value of the option to acquire the option to produce the  $k$ th output increment,  $G(\theta; k)$ , as:

$$\Delta G(\theta; k) = G\theta^{\beta_1} + H\theta^{\beta_2}, \quad (\text{IA.42})$$

where  $G$  and  $H$  are free parameters. Since  $\lim_{\theta \rightarrow 0} \Delta G(\theta; k) = 0$ , we immediately have  $H = 0$ . In contrast, its value upon an exercise is simply:  $\Delta G(\theta; k) = \Delta V(\theta; k) - I$ .

To find the values of  $G$  and  $\theta^*$ , the optimal exercise threshold, we ensure that the two component

solutions value-match with and smooth-paste into another. In particular, we require that:

$$B_O(\theta^*)^{\beta_2} + \frac{(\theta^*)}{\delta} - \frac{c_1 + c_2k + f}{r} - I = G(\theta^*)^{\beta_1}, \quad (\text{IA.43})$$

$$B_O\beta_2(\theta^*)^{\beta_2-1} + \frac{1}{\delta} = G\beta_1(\theta^*)^{\beta_1-1}, \quad (\text{IA.44})$$

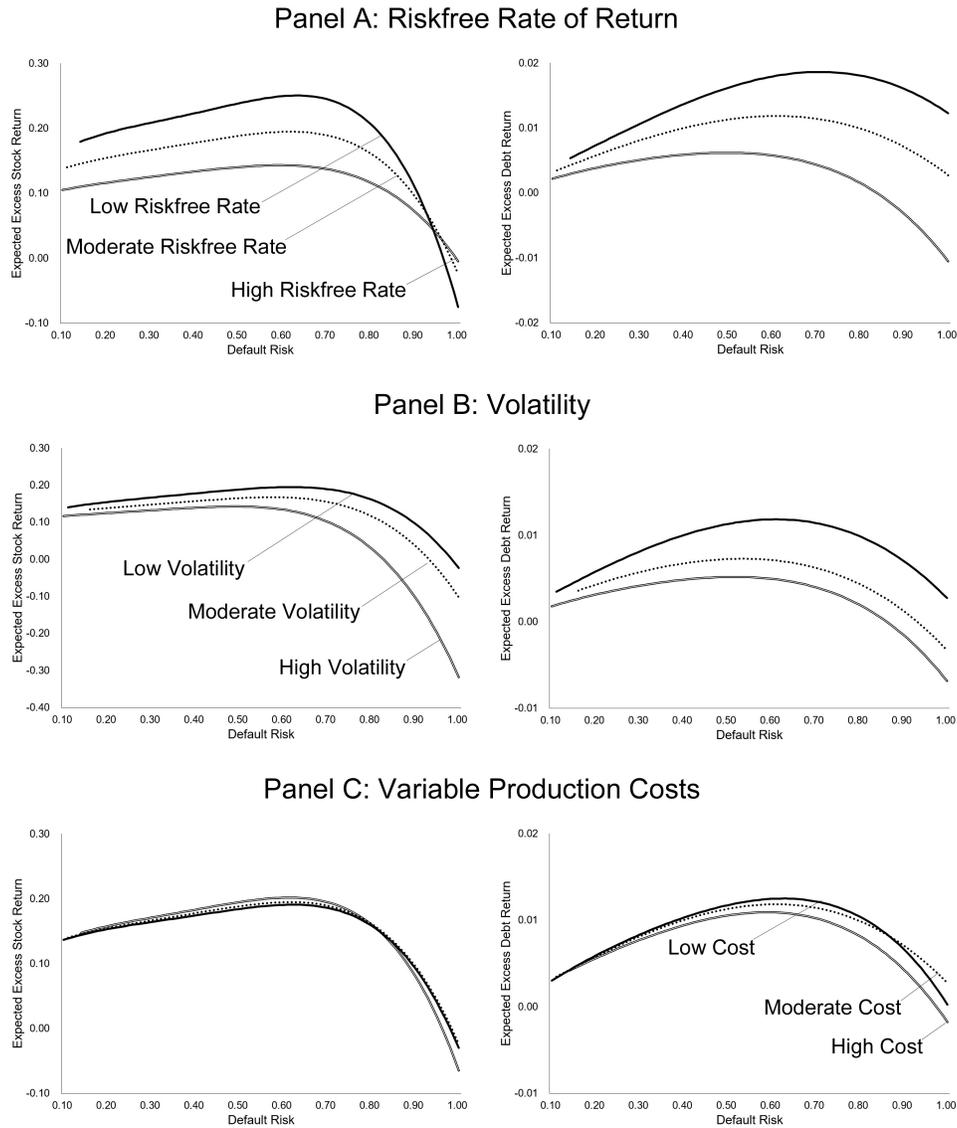
where Equation (IA.43) ensures that the value of the growth option is equal to its exercise payoff (i.e., the value of the corresponding option to produce minus the investment cost) at the optimal investment threshold, whereas Equation (IA.44) ensures that the partial derivatives of the option's value and its early exercise payoff are identical at that point. Solving Equation (IA.44) for  $G$ , we obtain:

$$G = \frac{1}{\beta_1} B_O(\theta^*)^{\beta_2-\beta_1} + \frac{(\theta^*)^{1-\beta_1}}{\beta_1\delta}. \quad (\text{IA.45})$$

Substituting  $G$  into Equation (IA.43), we then numerically solve for  $\theta^*$ .

### IA.7.2. Using Monte Carlo Simulations to Derive the Equity and Debt Values

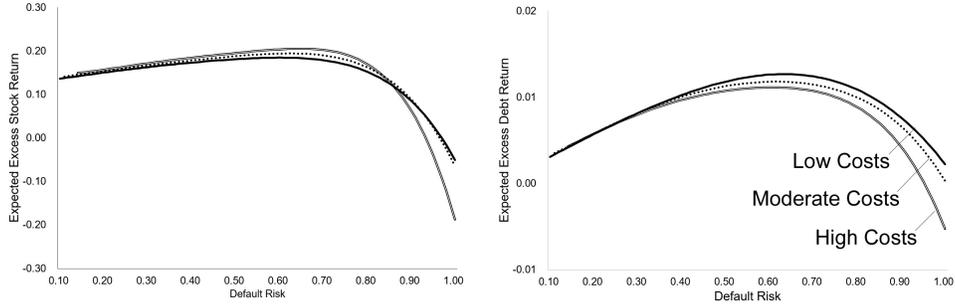
We use Monte Carlo simulations to evaluate the discounted risk-neutral expectation identifying a firm's debt value,  $D(\theta; T)$ , as we are unable to solve that expectation in closed-form (recall Equation (10) in our main paper). More specifically, we vary the initial output price,  $\theta$ , from 0.10 to 2.00 to create 100,000 daily sample output-price paths for each initial output price under the risk-neutral measure  $\mathbb{Q}$ . For each single path, we next determine the firm's optimal capacity utilization, expansion, and contraction decisions at the end of each day; calculate the sum of compounded-up disinvestment proceeds at time  $T$ ,  $S_T$ ; calculate the value of the firm's assets at that same time using the equations in Section IA.7.1.,  $V(\theta_T)$ ; and finally calculate  $e^{-rT} \min(C, V(\theta_T) + (1-q)S_T)$ . Averaging over the 100,000  $e^{-rT} \min(C, V(\theta_T) + (1-q)S_T)$  values, we obtain an approximation of the debt value,  $D(\theta; T)$ . As the equity value is the asset minus the debt value (i.e.,  $E(\theta; T) = V(\theta; T) - D(\theta; T)$ ), we also obtain an approximation of the equity value. Repeating those steps using the original initial output price plus or minus 0.0001, we use  $(D(\theta + 0.0001; T) - D(\theta - 0.0001; T))/0.0002$  and  $(E(\theta + 0.0001; T) - E(\theta - 0.0001; T))/0.0002$  to approximate the partial derivatives of the debt and equity value with



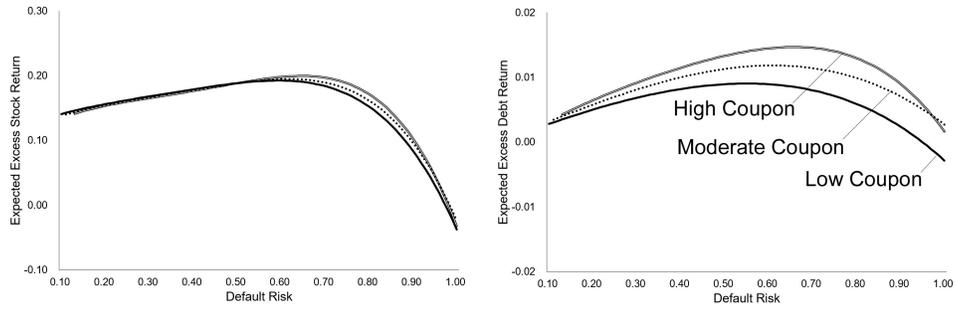
**Figure IA.7: The Default Risk-Expected Return Relations: Comparative Statics**

The figure offers comparative statics on the relations between the expected excess stock (left subpanels) and debt (right subpanels) return and default risk assuming a disinvestment gain,  $S$ , of eight and a fraction of disinvestment proceeds distributed to shareholders,  $q$ , equal to 0.10. In Panels A to F, we separately vary the riskfree rate of return  $r$ , output price volatility  $\sigma$ , variable production costs  $c_2$ , fixed production costs  $f$ , the coupon payment  $C$ , and the time-to-maturity  $T$ , respectively. See Section D in our main paper for more details about our basecase parameter value choices and Section IA.7.3. in this Internet Appendix for the high and low values.

Panel D: Fixed Production Costs



Panel E: Coupon



Panel F: Maturity Time

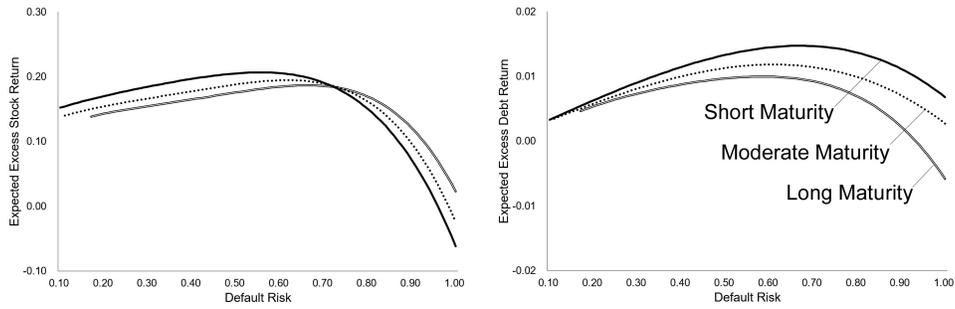


Figure IA.7: Continued

respect to the output price ( $\partial D(\theta; T)/\partial \theta$  and  $\partial E(\theta; T)/\partial \theta$ , respectively). Plugging the debt and equity values and their partial derivatives into Equation (11) of our main paper, we obtain the instantaneous expected excess stock and expected excess debt returns implied by our model.

### IA.7.3. Real Options Model Comparative Statics

We finally offer comparative statics on the model-implied relations between default risk and the expected stock and debt returns in Section IV of our main paper. Toward that goal, Figure IA.7 repeats Figure 6 in that paper, this time, however, separately setting the riskfree rate  $r$  (Panel A), the output price volatility  $\sigma$  (Panel B), the variable production costs  $c_2$  (Panel C), the fixed production costs  $f$  (Panel D), the coupon payment  $C$  (Panel E), and the maturity time  $T$  (Panel F) to a low, the basecase (for comparison), and a high value. More specifically, we choose  $r \in \{0.02, 0.04, 0.06\}$ ,  $\sigma \in \{0.45, 0.55, 0.65\}$ ,  $c_2 \in \{0.10, 0.30, 0.70\}$ ,  $f \in \{0.50, 0.70, 0.90\}$ ,  $C \in \{9.50, 10.00, 10.50\}$ , and  $T \in \{1.50, 2.00, 2.50\}$ .

Figure IA.7 shows that the negative (or more accurately: hump-shaped) relation between default risk and the expected stock or debt return is robust to parameter value variations. Notwithstanding, Panel A shows that a higher riskfree rate flattens the default risk-expected stock return relation, while making the default risk-expected debt return relation more negative. Conversely, Panels B to D suggest that a higher volatility or variable or fixed cost boosts the value of the firm's disinvestment options, rendering the relations between default risk and the expected returns more negative. Next, Panel E reveals that while a higher coupon exerts almost no effect on the default risk-expected stock return relation, it makes the default risk-expected debt return relation more positive (negative) over low (high) default risk values. Finally, Panel F indicates that while a longer maturity time hardly affects our main conclusions, it renders the default risk-expected debt return relation more negative because a longer maturity time allows the firm to disinvest more of its assets-in-place.

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**Table IA.1: Bond and Loan Sample Coverage**

In this table, we contrast our bond and loan samples (used in the stock-bond and stock-bond-loan-asset samples, respectively) with the CRSP-Compustat universe and also investigate credit-rating-based subsamples of those bond and loan samples. In particular, Panel A compares the entire CRSP-Compustat firm universe and the subuniverses of levered and non-levered firms (columns (1) to (3)), the entire sample of firms with bonds and the subsample of those with an asset value above \$100 million (columns (4) and (5)); and the entire sample of firms with loans and the subsample of those with an asset value above \$100 million (columns (6) and (7)) along their number of observations, mean and median market assets (in million \$), and median book and market leverage. For the bond and loan samples, it also calculates the median proportions of firms' short plus long-term debt book values captured by either the outstanding balances of their bonds or those of their bonds and loans. Panel B considers the same statistics calculated by credit-rating-subsamples in the bond (subpanel B.1) and the loan (subpanel B.2) samples. We compute market assets as the market value of common equity plus the book value of short and long-term debt and use S&P entity credit ratings to form the subsamples in Panel B.

Panel A: Sample Coverage Relative to the CRSP-Compustat Universe							
	CRSP/Compustat Universe			Bond Sample		Bond-Loan Sample	
	All	Leverage > 0	Leverage = 0	Leverage > 0	Lev. > 0 & Assets > \$100M	Leverage > 0	Lev. > 0 & Assets > \$100M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Observations	1,986,230	1,719,398	266,830	283,871	283,320	57,494	57,400
Average Market Assets	4,134.5	4,633.4	919.7	21,222.1	21,263.2	11,862.8	11,882.2
Median Market Assets	238.9	275.0	113.0	5,283.5	5,302.3	2,608.8	2,614.9
Median Book Leverage	1.38	1.51	1.00	1.79	1.79	2.04	2.04
Median Market Leverage	1.24	1.33	1.00	1.52	1.52	1.72	1.72
Debt% Covered by Bonds Alone				0.76	0.76	0.00	0.00
Debt% Covered by Bonds & Loans						0.93	0.93

(continued on next page)

Panel B: Sample Statistics by Entity-Rating Class

	# Obs.	Mean Market Assets	Median Market Assets	Median Book Leverage	Median Market Leverage	Debt% Covered By Bonds Alone	Debt% Covered By Bonds & Loans
Panel B.1: Bond Sample							
AAA	1,021	106,900.3	49,960.1	1.29	1.07	0.58	
AA	10,531	70,035.1	18,220.2	1.58	1.22	0.59	
A	75,960	39,923.3	12,017.8	1.71	1.36	0.66	
BBB	63,210	16,443.4	6,891.8	1.72	1.41	0.81	
BB	43,435	6,273.2	2,763.6	1.98	1.67	0.93	
B	24,235	4,271.2	1,533.0	2.28	2.14	0.99	
C	1,123	4,371.8	2,364.7	1.87	2.71	0.90	
Unrated	64,356	11,262.1	3,292.6	1.82	1.63	0.70	
Panel B.2: Loan Sample							
AAA	46	333,743.8	321,105.9	1.37	1.08	0.80	0.82
AA	236	448,775.5	618,719.4	3.80	2.44	0.39	0.39
A	1,685	109,831.8	20,886.6	1.53	1.22	0.69	0.81
BBB	2,218	36,887.7	11,670.1	1.71	1.34	0.53	0.96
BB	18,172	6,572.5	3,239.8	2.03	1.55	0.00	0.99
B	15,387	4,335.0	1,648.9	2.29	2.40	0.00	0.94
C	1,253	5,111.6	1,795.3	0.98	6.09	0.00	0.66
Unrated	18,497	5,479.3	2,124.3	2.05	1.68	0.00	0.90

**Table IA.2: Zero Price Changes and Correlations: Stock-Bond Sample**

This table presents the proportions of zero-bond-price-change observations (Panel A), the first three autocorrelations of stock and bond returns (Panel B), and the cross-correlations between stock and bond returns (Panel C) in the stock-bond sample. We report all these statistics both for the whole sample and credit-rating-based subsamples based on S&P entity credit ratings. In Panel A, “single bonds” gives the proportion of zero-bond-price-change bond-month observations, while “firm bond portfolios” reports the proportion of firm-month observations for which at least one bond of a firm does not change its price. In Panel B, subpanel B.1 gives average firm-level autocorrelations, while subpanel B.2 reports portfolio-level autocorrelations, where we value-weight the portfolios using either their stock or aggregate bond capitalizations.

Panel A: Proportion of Zero-Price-Change Bond Observations										
	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED	
Observations	1,712,230	6,262	108,496	677,645	433,379	136,057	58,604	3,264	288,523	
Single Bonds	1.70%	0.03%	0.63%	1.02%	1.09%	4.86%	5.86%	4.81%	2.28%	
Firm Bond Portfolios	6.24%	0.20%	4.63%	4.02%	3.63%	10.72%	10.83%	10.27%	7.13%	
Panel B: Stock and Bond Autocorrelations										
Panel B.1: Firm-Level Autocorrelation										
	Lag	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED
Stock	1	-0.01	-0.02	-0.03	-0.03	-0.02	-0.02	0.01	0.05	-0.01
	2	-0.01	-0.04	-0.04	-0.05	-0.04	-0.02	-0.01	-0.12	-0.01
	3	-0.01	-0.05	-0.03	-0.02	-0.02	-0.01	0.00	-0.08	-0.01
Bond	1	-0.02	0.14	0.07	0.01	-0.03	-0.06	-0.03	0.17	0.00
	2	-0.03	-0.08	-0.04	-0.04	-0.02	-0.03	-0.01	0.09	-0.04
	3	-0.02	-0.02	-0.04	-0.02	0.00	-0.02	0.00	0.02	-0.03
Panel B.2: Portfolio-Level Autocorrelation										
	Lag	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED
Stock	1	0.05	-0.05	-0.04	0.03	0.07	0.10	0.12	0.15	0.08
	2	-0.06	-0.04	-0.08	-0.07	-0.06	-0.04	-0.05	0.10	-0.06
	3	0.00	-0.01	0.03	0.01	0.02	0.00	0.09	0.07	-0.03
Bond	1	0.10	0.12	0.12	0.10	0.10	0.08	0.08	0.12	0.09
	2	-0.09	-0.10	-0.04	-0.10	-0.08	-0.10	-0.06	0.04	-0.10
	3	-0.07	-0.05	-0.09	-0.08	-0.04	-0.02	0.01	0.01	-0.04
Panel C: Cross-Correlations with Bond Returns										
	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED	
Bond, Equity	0.26	0.14	0.14	0.16	0.20	0.32	0.37	0.52	0.21	
Bond, Equity(-1)	0.06	-0.02	-0.03	0.00	0.05	0.07	0.10	0.14	0.06	
Bond, Equity(-2)	0.00	0.04	-0.02	-0.03	-0.01	0.00	0.01	0.02	0.00	
Bond, Equity(-3)	0.00	-0.01	-0.02	-0.02	0.00	0.00	0.01	0.02	-0.01	
Equity, Bond(-1)	0.04	0.02	0.04	0.02	0.01	0.05	0.07	0.04	0.04	
Equity, Bond(-2)	0.00	0.01	0.04	0.00	-0.02	0.01	0.02	0.05	0.01	
Equity, Bond(-3)	0.01	0.02	0.01	0.01	0.02	0.03	0.02	-0.02	0.00	

**Table IA.3: Zero Price Changes and Correlations: Stock-Bond-Loan-Asset Sample**

This table presents the proportions of zero-loan-price-change observations (Panel A), the first three autocorrelations of stock, bond, and loan returns (Panel B), and the cross-correlations between stock and either bond or loan returns (Panel C) in the stock-bond-loan-asset sample. We report all these statistics both for the whole sample and credit-rating-based subsamples based on S&P entity credit ratings. In Panel A, “single loans” gives the proportion of zero-loan-price-change loan-month observations, while “firm loan portfolios” reports the proportion of firm-month observations for which at least one loan of a firm does not change its price. We report the single-loan statistics separately for our quotes, transaction prices, and quotes conditional on at least one trade. In Panel B, subpanel B.1 gives average firm-level autocorrelations, while subpanel B.2 reports portfolio-level autocorrelations, where we value-weight the portfolios using either their stock or aggregate bond or loan capitalizations. In Panel C, we report the correlations with bond returns in Panel C.1 and those with loan returns in Panel C.2.

Panel A: Proportion of Zero-Price-Change Loan Observations									
	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED
Observations	234,240	46	416	3,974	30,041	34,116	4,620	3,268	157,759
Single Loans	33.91%	43.48%	44.95%	39.31%	26.72%	34.60%	47.79%	24.76%	34.74%
Quotes	34.19%	52.17%	45.43%	39.63%	47.88%	34.82%	27.02%	25.15%	35.03%
Transaction Prices	1.03%	2.17%	0.72%	1.36%	0.80%	1.16%	1.07%	0.73%	0.99%
Quotes   Trading	0.24%	6.52%	0.24%	0.33%	0.11%	0.21%	0.29%	0.40%	0.24%
Firm Loan Portfolios	42.99%	43.48%	50.00%	50.38%	56.73%	43.84%	35.54%	32.65%	43.77%

Panel B: Stock, Bond, and Loan Autocorrelations										
Panel B.1: Firm-Level Autocorrelation										
	Lag	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED
Stock	1	-0.01	-0.07	-0.11	0.03	-0.05	-0.05	0.00	-0.14	-0.02
	2	-0.02	-0.02	0.05	-0.11	-0.03	-0.02	-0.01	-0.10	-0.03
	3	-0.01	0.13	-0.18	-0.03	-0.03	-0.01	-0.01	0.02	-0.01
Bond	1	-0.04	0.02	0.06	0.07	-0.06	-0.11	0.00	0.16	-0.07
	2	-0.01	0.20	-0.02	-0.09	-0.04	-0.04	0.00	0.05	-0.01
	3	0.02	0.13	0.09	-0.01	0.02	0.02	0.02	0.04	0.00
Loan	1	0.06	0.02	-0.07	0.12	0.08	0.05	0.06	0.10	0.05
	2	0.00	-0.06	-0.03	0.02	0.08	-0.03	-0.02	-0.09	0.00
	3	-0.01	0.06	0.08	-0.01	0.13	-0.01	-0.01	0.05	-0.01

Panel B.2: Portfolio-Level Autocorrelation										
	Lag	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED
Stock	1	0.09	-0.07	-0.12	0.04	0.00	0.04	0.12	0.08	0.09
	2	-0.04	-0.02	-0.06	-0.10	-0.12	-0.07	-0.09	0.12	-0.04
	3	0.10	0.13	-0.15	0.10	0.10	0.02	0.14	0.06	0.06
Bond	1	0.02	0.03	0.09	0.09	0.05	-0.03	-0.03	0.04	0.03
	2	-0.13	0.20	0.04	-0.18	-0.10	-0.16	-0.04	0.05	0.04
	3	-0.03	0.13	0.18	-0.16	0.03	0.03	0.05	-0.02	0.00
Loan	1	0.43	0.02	0.24	0.30	0.24	0.35	0.47	0.32	0.31
	2	0.14	-0.06	-0.13	0.15	0.13	0.06	0.22	0.05	0.06
	3	0.05	0.06	-0.23	0.02	0.05	-0.06	0.09	0.10	-0.01

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Panel C: Cross-Correlations with Bond and Loan Returns

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Panel C.1: Cross-Correlations with Bond Returns

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	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED
Bond, Equity	0.30	0.26	0.08	0.09	0.21	0.31	0.32	0.45	0.24
Bond, Equity(-1)	0.08	0.13	0.02	0.05	0.02	0.02	0.09	0.13	0.06
Bond, Equity(-2)	0.00	0.24	-0.06	-0.02	-0.01	-0.01	-0.01	0.06	-0.02
Bond, Equity(-3)	0.01	0.20	0.21	0.02	-0.03	0.01	0.03	0.00	0.00
Equity, Bond(-1)	0.04	0.09	0.06	0.01	0.02	0.00	0.06	0.07	0.02
Equity, Bond(-2)	0.00	0.04	0.16	-0.04	-0.06	-0.03	-0.01	0.04	-0.01
Equity, Bond(-3)	0.02	-0.09	-0.02	0.03	0.00	0.04	0.04	0.01	-0.01

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Panel C.2: Cross-Correlations with Loan Returns

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	ALL	AAA	AA	A	BBB	BB	B	~C	UNRATED
Loan, Equity	0.22	0.05	0.18	0.14	0.20	0.23	0.25	0.24	0.21
Loan, Equity(-1)	0.15	-0.19	0.21	0.16	0.07	0.11	0.15	0.22	0.13
Loan, Equity(-2)	0.07	0.29	0.05	0.02	0.12	0.05	0.06	0.10	0.06
Loan, Equity(-3)	0.02	-0.25	0.05	-0.05	0.01	0.00	0.02	0.00	0.03
Equity, Loan(-1)	0.02	0.11	-0.15	0.07	0.03	-0.01	0.03	-0.08	0.03
Equity, Loan(-2)	0.02	-0.15	-0.06	0.08	0.01	0.01	0.02	0.02	0.02
Equity, Loan(-3)	0.03	0.16	0.18	0.02	0.00	0.05	0.02	0.04	0.02

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**Table IA.4: Stock and Bond Portfolio Characteristics**

The table offers the mean characteristics of stock and bond portfolios univariately sorted on distress risk in the stock-bond sample. Panels A and B focus on the stock and firm-specific bond portfolios, respectively. We first form an equally-weighted average of each characteristic first by portfolio and sample month and then average over our sample period. The stock characteristics include the market beta, market capitalization (size; in billion \$), the book-to-market ratio, the intermediate-term past (momentum) return, asset growth, and profitability. The bond characteristics include the bond market beta, the value-weighted average and aggregate bond capitalization (size; in billion \$), years-to-maturity, the credit rating, the coupon rate, downside risk, reversal, the liquidity beta, and illiquidity. See Table A1 in Appendix A at the end of the main paper for details about the characteristics also used in the main paper. The coupon rate is a bond's coupon-to-price ratio, its liquidity beta its loading on the orthogonalized aggregate signed volume coefficient from first-stage regressions (see Lin et al. (2011)), and its illiquidity its daily-price-change autocovariance (see Bao et al. (2011)).

	Distress Risk Decile Portfolios									
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
Panel A: Stock Portfolio Characteristics										
Market Beta	0.82	0.81	0.79	0.77	0.76	0.75	0.74	0.75	0.78	0.88
Market Size	3.88	5.34	5.75	5.58	4.90	4.30	3.49	2.56	1.80	1.02
Book-to-Market	0.57	0.54	0.56	0.58	0.61	0.64	0.67	0.69	0.69	0.67
Momentum	0.07	0.10	0.10	0.10	0.09	0.09	0.09	0.08	0.07	0.03
Asset Growth	0.17	0.16	0.14	0.14	0.13	0.13	0.13	0.14	0.15	0.18
Profitability	0.38	0.37	0.35	0.33	0.30	0.28	0.25	0.23	0.23	0.23
Panel B: Bond Portfolio Characteristics										
Bond Market Beta	0.42	0.45	0.46	0.47	0.47	0.47	0.46	0.45	0.44	0.43
Market Size	0.36	0.36	0.36	0.36	0.36	0.36	0.37	0.36	0.36	0.34
Total Market Size	1.79	2.02	2.25	2.36	2.43	2.48	2.7	2.52	2.19	1.53
Maturity	9.51	10.00	10.20	10.21	10.11	10.01	9.66	9.24	8.75	8.04
Credit Rating	7.93	7.59	7.53	7.56	7.67	7.78	7.97	8.20	8.71	10.02
Coupon	7.51	7.32	7.29	7.32	7.36	7.41	7.51	7.62	7.84	8.47
Downside Risk	1.64	1.63	1.57	1.62	1.63	1.64	1.67	1.74	1.84	2.40
Reversal	0.90	0.89	0.84	0.83	0.82	0.79	0.77	0.75	0.71	0.40
Liquidity Beta	0.03	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.04	0.07
Illiquidity	0.25	0.20	0.20	0.25	0.26	0.24	0.32	0.32	0.31	0.53

**Table IA.5: Stock and Bond Long Horizon Distress Premiums**

The table offers the risk-adjusted stock (Panel A) and bond (Panel B) mean returns of the value or equally-weighted or the [Fama and MacBeth \(1973\)](#) regression high-minus-low distress decile spread portfolio separately for each month over the year after the portfolio formation date in the stock-bond sample. To create the first two spread portfolios, we sort our sample stocks or firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm) into portfolios according to the decile breakpoints of [Campbell et al. \(2008\)](#) distress risk at the end of month  $t - 1$ . We then value or equally weight the portfolios and hold them over each month from  $t$  to  $t + 11$ , where we use a firm's total stock or bond capitalization to construct the value-weights. We finally form the spread portfolios as long the top distress decile portfolio and short the bottom and compute their FF6S (stocks) or SB14 (bonds) alphas. Conversely, we construct the [Fama and MacBeth \(1973\)](#) risk-adjusted spread portfolio return from a regression of the stock or bond return over each month from  $t$  to  $t + 11$  on nine distress decile portfolio dummy variables omitting the dummy for the first decile and controls, choosing the coefficient of the decile-10 dummy as the risk-adjusted spread portfolio return. In Panel B, we use both standard (Ret=S) and [Bartram, Grinblatt and Nozawa \(2025; Ret=BGN\)](#) returns to create the spread portfolio returns. Plain numbers are monthly estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics with a twelve-month lag length.

		Month After Portfolio Formation											
Ret		1	2	3	4	5	6	7	8	9	10	11	12
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Stocks													
Value-Weighted Sorts	S	-0.98 [-2.25]	-1.05 [-3.55]	-1.01 [-3.34]	-0.60 [-2.32]	-0.64 [-2.51]	-1.05 [-3.70]	-0.61 [-2.26]	-0.49 [-1.66]	-0.47 [-2.25]	-0.46 [-1.72]	-0.94 [-3.31]	-0.03 [-0.08]
Equally-Weighted Sorts	S	-0.84 [-3.73]	-1.08 [-4.39]	-1.22 [-5.81]	-0.95 [-5.60]	-0.81 [-4.59]	-0.97 [-5.40]	-0.67 [-4.09]	-0.46 [-2.63]	-0.63 [-4.46]	-0.48 [-3.04]	-0.61 [-3.60]	-0.35 [-2.01]
FM Regressions	S	-0.55 [-2.27]	-1.07 [-4.98]	-1.04 [-5.82]	-0.64 [-3.93]	-0.70 [-4.95]	-0.67 [-4.76]	-0.48 [-3.56]	-0.25 [-1.76]	-0.42 [-3.35]	-0.23 [-1.71]	-0.32 [-2.20]	-0.21 [-1.61]
Panel B: Bonds													
Value-Weighted Sorts	S	-0.47 [-7.51]	-0.27 [-4.53]	-0.29 [-6.24]	-0.20 [-4.03]	-0.15 [-1.77]	-0.19 [-3.47]	-0.15 [-2.92]	-0.06 [-0.96]	-0.13 [-2.70]	-0.12 [-2.25]	-0.19 [-2.79]	-0.14 [-2.38]
Equally-Weighted Sorts	S	-0.41 [-7.27]	-0.23 [-4.72]	-0.22 [-5.81]	-0.16 [-3.21]	-0.17 [-2.34]	-0.14 [-2.54]	-0.12 [-2.75]	-0.05 [-0.96]	-0.10 [-2.25]	-0.13 [-2.36]	-0.18 [-3.06]	-0.13 [-2.66]
FM Regressions	S	-0.39 [-6.04]	-0.13 [-3.19]	-0.07 [-1.92]	-0.05 [-1.19]	-0.06 [-1.86]	-0.02 [-0.63]	-0.02 [-0.51]	0.02 [0.48]	-0.03 [-0.80]	-0.02 [-0.53]	-0.04 [-1.04]	-0.04 [-1.13]
Value-Weighted Sorts	BGN	-0.47 [-7.59]	-0.26 [-4.24]	-0.30 [-6.52]	-0.21 [-4.01]	-0.11 [-1.20]	-0.19 [-3.52]	-0.15 [-2.96]	-0.21 [-1.39]	0.01 [0.10]	-0.09 [-1.62]	-0.19 [-2.72]	-0.12 [-1.99]
Equally-Weighted Sorts	BGN	-0.41 [-7.23]	-0.23 [-4.63]	-0.21 [-5.75]	-0.16 [-3.33]	-0.18 [-2.40]	-0.14 [-2.56]	-0.11 [-2.75]	-0.05 [-1.07]	-0.09 [-2.06]	-0.13 [-2.45]	-0.17 [-2.97]	-0.13 [-2.60]
FM Regressions	BGN	-0.38 [-5.98]	-0.12 [-3.04]	-0.06 [-1.46]	-0.04 [-1.00]	-0.06 [-1.57]	-0.01 [-0.38]	0.00 [-0.04]	0.02 [0.72]	0.00 [-0.11]	-0.02 [-0.53]	-0.02 [-0.48]	-0.03 [-0.86]

**Table IA.6: Bond Portfolios Double-Sorted on Distress and Credit Ratings**

The table presents the SB14 alphas of single-bond portfolios double-sorted on corporate distress risk and bond credit ratings. In Panel A, we first sort our sample bonds into portfolios according to whether a bond's most recent rating at the end of month  $t - 1$  is high investment grade (rating value: 1 to 4), low investment grade (5 to 10), or speculative (above 10). Within each rating portfolio, we next sort them into portfolios according to the tercile breakpoints of [Campbell et al. \(2008\)](#) distress risk at the end of month  $t - 1$ . In Panel B, we reverse the order, first sorting into distress and then credit rating portfolios. We value-weight the portfolios and hold them over month  $t$ , using a bond's market capitalization as weight. Within each rating (distress) portfolio, we form a portfolio long the top distress (lowest rating) portfolio and short the bottom (highest rating) portfolio. The table reports the mean number of assets and the alpha of the SB14 stock-bond factor model. Plain numbers are monthly estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics with a twelve-month lag length.

Panel A: Dependent Sort on Credit Rating and Distress Risk						
Distress Risk	High IG		Low IG		Speculative	
	Obs	Alpha	Obs	Alpha	Obs	Alpha
	(1)	(2)	(3)	(4)	(5)	(6)
1 (Low Distress)	399	0.13	609	0.18	204	0.34
2	405	0.09	616	0.06	206	0.14
3 (High Distress)	425	0.06	622	0.06	210	-0.10
High-Low		-0.07		-0.11		-0.44
$t$ -statistic		[-2.08]		[-3.62]		[-6.84]
Panel B: Dependent Sort on Distress Risk and Credit Rating						
Credit Rating	Distress Tercile 1		Distress Tercile 2		Distress Tercile 3	
	Obs	Alpha	Obs	Alpha	Obs	Alpha
	(1)	(2)	(3)	(4)	(5)	(6)
High IG	439	0.13	447	0.15	344	0.04
Low IG	609	0.18	652	0.06	587	0.01
Speculative	165	0.34	156	0.18	300	-0.03
Speculative-High		0.21		0.03		-0.07
$t$ -statistic		[4.65]		[0.34]		[-1.30]

**Table IA.7: Stock, Bond, Loan, and Firm-Asset Portfolio Characteristics**

The table offers the mean characteristics of stock, bond, loan, and firm-asset portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample. Panels A to D focus on the stock, firm-specific bond portfolios, firm-specific loan portfolios, and firm-specific asset portfolios, respectively. We first form an equally-weighted average of each characteristic first by portfolio and sample month and then average over our sample period. The stock characteristics include the market beta, market capitalization (size; in billion), the book-to-market ratio, the intermediate-term past (momentum) return, asset growth, and profitability. The bond characteristics include the bond market beta, the value-weighted average and aggregate bond capitalization (size; in billion \$), years-to-maturity, the credit rating, the coupon rate, downside risk, reversal, the liquidity beta, and illiquidity. The loan characteristics include the value-weighted average and aggregate loan capitalization (size; in billion \$) and years-to-maturity. The firm-asset characteristics include the total firm-asset capitalization. See Table A1 in Appendix A at the end of the main paper for details about the characteristics also used in the main paper. The coupon rate is a bond's coupon-to-price ratio, its liquidity beta its loading on the orthogonalized aggregate signed volume coefficient from first-stage regressions (see Lin et al. (2011)), and its illiquidity its daily-price-change autocovariance (see Bao et al. (2011)).

	Distress Risk Quintile Portfolios				
	1 (Low)	2	3	4	5 (High)
Panel A: Stock Portfolio Characteristics					
Market Beta	0.77	0.82	0.89	1.01	1.27
Market Size	3.47	3.11	2.52	1.78	0.75
Book-to-Market	0.45	0.48	0.52	0.60	0.72
Momentum	0.08	0.06	0.03	-0.03	-0.23
Asset Growth	0.14	0.13	0.13	0.13	0.11
Profitability	0.30	0.27	0.26	0.26	0.25
Panel B: Bond Portfolio Characteristics					
Bond Market Beta	0.27	0.28	0.32	0.33	0.42
Market Size	0.55	0.55	0.55	0.54	0.44
Total Market Size	3.00	3.79	3.95	3.72	1.94
Maturity	7.31	7.08	6.81	6.54	6.35
Credit Rating	11.70	12.25	12.78	13.41	14.75
Coupon	7.26	7.41	7.66	7.93	8.40
Downside Risk	1.60	1.76	2.01	2.36	3.59
Reversal	1.02	1.03	0.99	0.76	-0.49
Liquidity Beta	0.07	0.08	0.11	0.12	0.18
Illiquidity	0.36	0.49	0.57	0.87	1.69
Panel C: Loan Portfolio Characteristics					
Market Size	0.43	0.46	0.49	0.49	0.43
Total Market Size	0.52	0.58	0.61	0.63	0.54
Maturity	4.11	4.10	4.12	4.12	4.01
Panel D: Asset Portfolio Characteristics					
Market Size	5.28	5.01	4.51	3.74	2.35

**Table IA.8: Stock, Bond, Loan, and Firm-Asset Long Horizon Distress Premiums**

The table offers the risk-adjusted stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) mean returns of the value or equally-weighted or the [Fama and MacBeth \(1973\)](#) regression high-minus-low distress quintile spread portfolio separately for each month over the year after the portfolio formation date in the stock-bond-loan-asset sample. To create the first two spread portfolios, we sort our sample stocks, firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm), firm-specific loan portfolios (i.e., the value-weighted portfolios of all outstanding loans by firm), and firm-specific asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of [Campbell et al. \(2008\)](#) distress risk at the end of month  $t - 1$ . We then value or equally weight the portfolios and hold them over each month from  $t$  to  $t + 11$ , where we use a firm's total stock, bond, loan, and firm-asset capitalization to construct the value-weights. We finally form the spread portfolios as long the top distress quintile portfolio and short the bottom and compute their FF6S (stocks), SB14 (bonds), SB14 (loans), and SB17 (firm assets) alphas. Conversely, we construct the [Fama and MacBeth \(1973\)](#) risk-adjusted spread portfolio return from a regression of the stock, bond, loan, or firm-asset return over each month from  $t$  to  $t + 11$  on four distress quintile portfolio dummy variables omitting the dummy for the first quintile and controls, choosing the coefficient of the quintile-5 dummy as the risk-adjusted spread portfolio return. In Panels B, C, and D, we use both standard (Ret=S) and [Bartram, Grinblatt and Nozawa \(2025; Ret=BGN\)](#) returns to create the spread portfolio returns. Plain numbers are monthly estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics with a twelve-month lag length.

		Month After Portfolio Formation												
Ret		1	2	3	4	5	6	7	8	9	10	11	12	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Panel A: Stocks														
52	Value-Weighted Sorts	S	-1.12 [-2.49]	-0.92 [-2.54]	-0.78 [-1.96]	-0.13 [-0.31]	-0.38 [-1.39]	0.18 [0.69]	-0.05 [-0.15]	-0.30 [-0.78]	0.08 [0.21]	-0.33 [-1.10]	0.14 [0.50]	0.54 [1.85]
	Equally-Weighted Sorts	S	-0.79 [-2.20]	-0.65 [-1.89]	-0.32 [-0.95]	-0.17 [-0.44]	-0.18 [-0.77]	0.33 [1.20]	0.05 [0.17]	-0.16 [-0.58]	0.11 [0.44]	0.02 [0.07]	0.04 [0.18]	0.56 [2.87]
	FM Regressions	S	-0.42 [-1.00]	-0.79 [-2.12]	-0.23 [-0.72]	0.19 [0.81]	0.17 [0.68]	0.09 [0.47]	0.30 [1.31]	0.06 [0.28]	-0.11 [-0.55]	-0.07 [-0.34]	0.20 [1.05]	0.54 [2.68]
Panel B: Bonds														
	Value-Weighted Sorts	S	-0.87 [-3.52]	-0.44 [-2.27]	-0.45 [-3.06]	-0.22 [-1.47]	-0.15 [-0.74]	-0.38 [-2.73]	-0.08 [-0.49]	-0.13 [-0.79]	-0.16 [-1.17]	-0.04 [-0.22]	0.00 [0.03]	0.03 [0.20]
	Equally-Weighted Sorts	S	-0.79 [-3.61]	-0.22 [-1.21]	-0.17 [-1.08]	-0.22 [-1.57]	-0.07 [-0.37]	-0.19 [-1.29]	-0.04 [-0.31]	-0.12 [-0.91]	-0.10 [-0.81]	-0.04 [-0.32]	-0.05 [-0.43]	0.06 [0.62]
	FM Regressions	S	-0.73 [-3.38]	-0.15 [-1.31]	-0.15 [-1.27]	-0.14 [-1.01]	0.00 [0.01]	0.03 [0.26]	-0.08 [-0.94]	-0.03 [-0.43]	0.00 [0.01]	0.02 [0.29]	-0.02 [-0.18]	0.09 [1.24]
	Value-Weighted Sorts	BGN	-0.95 [-3.73]	-0.44 [-2.76]	-0.46 [-3.02]	-0.37 [-2.26]	-0.26 [-1.01]	-0.66 [-2.43]	-0.23 [-1.29]	-0.14 [-0.80]	-0.31 [-1.41]	-0.19 [-0.86]	-0.15 [-0.89]	-0.07 [-0.37]

(continued on next page)

Panel B: Bonds (continued)

Equally-Weighted Sorts	BGN	-0.85	-0.32	-0.23	-0.27	-0.27	-0.46	-0.19	-0.08	-0.22	-0.17	-0.13	-0.01
		[-3.78]	[-2.12]	[-1.59]	[-2.14]	[-1.31]	[-1.93]	[-1.10]	[-0.65]	[-1.15]	[-0.83]	[-0.86]	[-0.06]
FM Regressions	BGN	-0.99	0.00	-0.78	-0.10	-0.12	0.22	0.06	-0.02	-0.01	-0.10	-0.12	0.26
		[-2.86]	[-0.00]	[-1.09]	[-0.75]	[-0.91]	[1.26]	[0.60]	[-0.26]	[-0.05]	[-0.87]	[-0.93]	[1.40]

Panel C: Loans

Value-Weighted Sorts	S	-0.36	-0.27	-0.29	-0.21	-0.14	-0.16	-0.10	-0.02	0.00	-0.03	0.02	0.01
		[-2.89]	[-2.40]	[-2.97]	[-2.04]	[-1.20]	[-1.33]	[-1.03]	[-0.21]	[-0.04]	[-0.30]	[0.16]	[0.09]
Equally-Weighted Sorts	S	-0.35	-0.22	-0.26	-0.21	-0.15	-0.07	-0.04	-0.06	-0.04	-0.02	-0.03	0.03
		[-2.99]	[-2.36]	[-2.99]	[-2.37]	[-1.55]	[-0.69]	[-0.53]	[-0.79]	[-0.60]	[-0.24]	[-0.29]	[0.49]
FM Regressions	S	-0.28	-0.19	-0.15	-0.08	-0.03	-0.03	-0.01	-0.02	0.03	0.02	-0.03	0.08
		[-2.28]	[-2.27]	[-2.25]	[-1.09]	[-0.42]	[-0.57]	[-0.23]	[-0.34]	[0.89]	[0.29]	[-0.52]	[1.37]
Value-Weighted Sorts	BGN	-0.32	-0.23	-0.33	-0.17	-0.16	-0.25	-0.11	0.01	-0.03	-0.05	-0.05	-0.02
		[-3.21]	[-2.55]	[-4.23]	[-1.86]	[-1.83]	[-2.83]	[-1.43]	[0.11]	[-0.42]	[-0.55]	[-0.38]	[-0.34]
Equally-Weighted Sorts	BGN	-0.29	-0.18	-0.26	-0.14	-0.15	-0.12	-0.06	-0.03	-0.04	-0.02	-0.06	0.01
		[-2.98]	[-2.43]	[-3.44]	[-1.76]	[-1.88]	[-1.40]	[-0.72]	[-0.34]	[-0.64]	[-0.28]	[-0.60]	[0.17]
FM Regressions	BGN	-0.22	-0.12	-0.13	-0.02	-0.02	-0.03	0.01	0.00	0.05	0.02	-0.05	0.10
		[-2.18]	[-2.03]	[-2.25]	[-0.29]	[-0.41]	[-0.66]	[0.22]	[-0.04]	[1.43]	[0.44]	[-0.71]	[1.94]

Panel D: Firm Assets

Value-Weighted Sorts	S	-0.80	-0.67	-0.30	-0.09	-0.22	-0.12	0.01	-0.24	-0.33	-0.08	0.01	0.36
		[-2.64]	[-2.79]	[-1.28]	[-0.38]	[-1.17]	[-0.65]	[0.06]	[-1.17]	[-1.51]	[-0.48]	[0.04]	[2.28]
Equally-Weighted Sorts	S	-0.58	-0.72	-0.05	-0.06	-0.06	-0.01	0.05	-0.19	-0.27	0.05	-0.02	0.39
		[-3.02]	[-3.13]	[-0.30]	[-0.29]	[-0.22]	[-0.06]	[0.25]	[-1.14]	[-1.81]	[0.42]	[-0.14]	[3.63]
FM Regressions	S	-0.54	-0.54	-0.44	-0.11	-0.21	-0.21	-0.01	-0.12	-0.21	-0.08	-0.18	0.25
		[-2.52]	[-2.90]	[-2.53]	[-0.85]	[-1.39]	[-1.93]	[-0.04]	[-0.85]	[-1.76]	[-0.83]	[-1.31]	[2.12]
Value-Weighted Sorts	BGN	-0.59	-0.41	-0.36	-0.06	-0.28	-0.29	0.00	-0.21	-0.19	0.10	-0.05	0.26
		[-2.20]	[-1.83]	[-1.53]	[-0.27]	[-1.51]	[-1.37]	[0.01]	[-1.30]	[-1.07]	[0.60]	[-0.35]	[1.72]
Equally-Weighted Sorts	BGN	-0.36	-0.53	-0.09	0.03	-0.14	-0.22	0.02	-0.18	-0.21	0.16	-0.04	0.32
		[-2.21]	[-2.79]	[-0.53]	[0.17]	[-0.63]	[-0.92]	[0.12]	[-1.37]	[-1.48]	[1.20]	[-0.38]	[2.50]
FM Regressions	BGN	-0.42	-0.37	-0.45	-0.04	-0.29	-0.25	0.06	-0.07	-0.10	-0.08	-0.21	0.24
		[-2.41]	[-1.88]	[-2.76]	[-0.29]	[-2.06]	[-2.81]	[0.50]	[-0.52]	[-0.75]	[-0.85]	[-1.70]	[2.37]

**Table IA.9: Bond Distress Portfolios: Transaction-Price Subsample**

The table offers the SB14 and SB15 alphas of bond portfolios univariately sorted on distress risk in the stock-bond sample exclusively using TRACE transaction prices to calculate bond returns. Panels A and B focus on standard and Bartram et al. (2025; BGN) bond returns, respectively. We sort our sample firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm) into portfolios according to the decile breakpoints of Campbell et al. (2008) distress risk at the end of month  $t - 1$ . We value (columns (1) and (2)) or equally ((3) and (4)) weight the portfolios and hold them over month  $t$ , where we use a firm’s total bond capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the fifth (top) [top] decile portfolio and short the bottom (fifth) [bottom] (“Middle–Low” (“High–Middle”) [“High–Low”]). SB14 and SB15 indicate the 14-factor stock-bond model and the same model plus a liquidity factor based on Bao et al.’s (2011) bond illiquidity proxy, respectively. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987)  $t$ -statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

	Value-Weighted Portfolios		Equally-Weighted Portfolios	
	Monthly Alpha	Monthly Alpha (incl. Liquidity Control)	Monthly Alpha	Monthly Alpha (incl. Liquidity Control)
	(1)	(2)	(3)	(4)
Panel A: Month-End to Month-End Bond Returns (Mean Monthly # Per Portfolio: 70)				
Middle–Low	–0.09 [–2.29]	–0.09 [–2.36]	–0.06 [–2.11]	–0.06 [–2.28]
High–Middle	–0.44 [–4.61]	–0.43 [–4.34]	–0.50 [–4.97]	–0.49 [–4.82]
High–Low	–0.53 [–5.80]	–0.52 [–5.69]	–0.56 [–6.04]	–0.55 [–5.77]
Alpha Factors	SB14	SB15	SB14	SB15
Panel B: Bartram, Grinblatt and Nozawa (2025) Bond Returns (Mean Monthly # Per Portfolio: 83)				
Middle–Low	–0.08 [–2.61]	–0.08 [–2.62]	–0.07 [–3.03]	–0.07 [–3.00]
High–Middle	–0.41 [–4.67]	–0.40 [–4.31]	–0.42 [–4.77]	–0.41 [–4.53]
High–Low	–0.49 [–5.66]	–0.48 [–5.43]	–0.49 [–5.27]	–0.48 [–5.03]
Alpha Factors	SB14	SB15	SB14	SB15

**Table IA.10: Bond Regressions on Distress Risk: Transaction-Price Subsample**

The table offers the results from [Fama and MacBeth \(1973\)](#) regressions of the excess returns of all, investment-grade (IG), and speculative-grade (SG) firm-specific bond portfolios over month  $t$  on two distress dummy variables and controls at the end of month  $t - 1$  in the stock-bond sample exclusively using TRACE transaction prices to calculate bond returns and controlling for illiquidity and liquidity risk in columns (2), (4), (6), and (8). We create the bond portfolios by forming value-weighted portfolios of all outstanding bonds by firm. Investment (speculative) grade bonds have a rating equal to or above (below) BBB- at the end of month  $t - 1$ . The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if [Campbell et al. \(2008\)](#) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls also used in the main paper. Bond illiquidity is a bond's daily-price-change autocovariance (see [Bao et al. \(2011\)](#)), while its liquidity beta is its loading on the orthogonalized aggregate signed volume coefficient obtained from first-stage regressions (see [Lin et al. \(2011\)](#)). Plain numbers are monthly premium estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics calculated with a twelve-month lag length. The columns labelled "ME-ME" ("BGN") rely on standard ([Bartram et al. \(2025; BGN\)](#)) returns.

	All Bonds	All Bonds	All Bonds	All Bonds	IG Bonds	IG Bonds	SG Bonds	SG Bonds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>HighDistress</i>	-0.40 [-4.24]	-0.42 [-4.41]	-0.32 [-3.82]	-0.33 [-4.01]	-0.21 [-2.69]	-0.21 [-2.69]	-0.59 [-4.93]	-0.59 [-5.30]
<i>LowDistress</i>	0.07 [2.85]	0.08 [3.09]	0.06 [3.19]	0.07 [3.39]	0.07 [2.92]	0.07 [3.10]	0.15 [3.30]	0.15 [3.52]
<i>MarketBeta</i>	0.03 [0.53]	0.02 [0.40]	0.05 [1.51]	0.05 [1.42]	0.03 [0.50]	0.02 [0.36]	-0.02 [-0.36]	-0.02 [-0.29]
<i>MarketSize</i>	-0.04 [-1.76]	-0.04 [-1.92]	-0.03 [-1.57]	-0.03 [-1.98]	-0.01 [-0.57]	-0.01 [-0.48]	-0.02 [-0.84]	-0.04 [-1.29]
<i>BookToMarket</i>	-0.02 [-1.00]	-0.02 [-1.31]	0.00 [-0.28]	-0.01 [-0.51]	0.00 [0.22]	0.00 [0.35]	-0.01 [-0.19]	-0.02 [-0.71]
<i>Momentum</i>	0.08 [0.85]	0.10 [1.20]	0.09 [1.11]	0.11 [1.52]	0.18 [2.74]	0.19 [3.21]	-0.04 [-0.33]	-0.03 [-0.27]
<i>AssetGrowth</i>	0.01 [0.33]	0.01 [0.26]	0.06 [1.47]	0.05 [1.28]	0.00 [-0.03]	0.01 [0.25]	-0.02 [-0.37]	-0.03 [-0.41]
<i>Profitability</i>	-0.02 [-0.28]	-0.05 [-0.90]	-0.05 [-0.80]	-0.07 [-1.32]	-0.07 [-1.47]	-0.08 [-1.54]	0.08 [0.55]	0.06 [0.39]
<i>BondMarketBeta</i>	0.27 [1.24]	0.22 [1.12]	0.09 [0.43]	0.03 [0.13]	0.45 [1.29]	0.42 [1.18]	0.20 [0.76]	0.19 [0.82]
<i>BondSize</i>	-0.07 [-3.17]	-0.06 [-2.92]	-0.17 [-5.54]	-0.16 [-5.49]	-0.07 [-3.41]	-0.07 [-3.55]	-0.11 [-2.90]	-0.10 [-2.90]
<i>BondMaturity</i>	0.14 [2.35]	0.14 [2.29]	0.13 [2.91]	0.13 [3.00]	0.13 [2.23]	0.12 [2.16]	0.21 [2.45]	0.20 [2.42]
<i>BondCreditRating</i>	0.17 [2.77]	0.14 [2.53]	0.10 [1.48]	0.08 [1.34]	0.10 [2.08]	0.09 [1.92]	0.60 [2.28]	0.52 [1.99]
<i>BondDownsideRisk</i>	3.70 [2.85]	3.12 [2.56]	3.84 [3.14]	3.50 [3.20]	3.40 [2.83]	3.32 [2.79]	3.62 [2.54]	3.32 [2.41]

(continued on next page)

<i>BondReversal</i>	-21.60	-22.06	-16.91	-17.29	-24.32	-24.73	-18.65	-19.00
	[-11.39]	[-12.39]	[-10.75]	[-12.03]	[-11.84]	[-12.75]	[-9.83]	[-10.14]
<i>BondIlliquidity</i>		0.03		0.00		0.04		0.01
		[1.11]		[-0.10]		[1.56]		[0.47]
<i>BondLiquidityBeta</i>		0.13		0.04		0.14		0.07
		[1.13]		[0.48]		[1.46]		[0.63]
Return Type	ME-ME	ME-ME	BGN	BGN	ME-ME	ME-ME	ME-ME	ME-ME

**Table IA.11: Stock, Bond, Loan, & Asset Distress Portfolios: Transaction-Price Sub-sample**

The table offers the monthly alphas of stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample exclusively using TRACE transaction prices to calculate bond returns. The first and second subpanels in Panels B to D focus on standard and Bartram et al. (2025; BGN) bond returns, respectively. We sort our sample firm-specific stocks, bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm), loan portfolios (i.e., the value-weighted portfolios of all outstanding loans by firm), firm-asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month  $t - 1$ . We value (columns (1) and (2)) or equally ((3) and (4)) weight the portfolios and hold them over month  $t$ , where we use a firm's total stock, bond, loan, and firm-asset capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] ("Middle-Low" ("High-Middle") ["High-Low"]). FF6S and FF7S indicate the Fama and French (2016) six-factor model and the same model plus a stock liquidity factor; SB14 and SB15 indicate the 14-factor stock-bond model and the same model plus a bond liquidity factor; and SB17 and SB18 indicate the 17-factor stock-bond model and the same model plus a stock and bond liquidity factor, all respectively. The stock liquidity factor is constructed from Pástor and Stambaugh's (2003) liquidity proxy, whereas the bond liquidity factor is constructed from Bao et al.'s (2011) illiquidity proxy. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987)  $t$ -statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

	Value-Weighted Portfolios		Equally-Weighted Portfolios	
	Monthly Alpha	Monthly Alpha (incl. Liquidity Control)	Monthly Alpha	Monthly Alpha (incl. Liquidity Control)
	(1)	(2)	(3)	(4)
Panel A: Stock Returns (Mean Monthly # Per Portfolio: 33)				
Middle-Low	0.20 [0.97]	0.25 [1.19]	0.30 [1.74]	0.32 [1.91]
High-Middle	-0.58 [-1.53]	-0.59 [-1.58]	-0.68 [-1.90]	-0.82 [-2.39]
High-Low	-0.38 [-1.00]	-0.34 [-0.86]	-0.38 [-1.05]	-0.50 [-1.43]
Alpha Factors	FF6S	FF7S	FF6S	FF7S
Panel B: Firm-Level Bond Returns				
Panel B.1: Month-End to Month-End Bond Returns (Mean Monthly # Per Portfolio: 17)				
Middle-Low	-0.13 [-1.14]	-0.14 [-1.15]	-0.23 [-2.19]	-0.22 [-2.22]
High-Middle	-0.73 [-3.78]	-0.72 [-3.67]	-0.54 [-2.88]	-0.55 [-2.93]
High-Low	-0.86 [-5.11]	-0.85 [-5.11]	-0.76 [-4.80]	-0.77 [-4.73]
Panel B.2: Bartram, Grinblatt and Nozawa (2025) Bond Returns (Mean Monthly # Per Portfolio: 21)				
Middle-Low	-0.09 [-1.14]	-0.10 [-1.17]	-0.14 [-1.84]	-0.15 [-1.92]

(continued on next page)

Panel B.2: <a href="#">Bartram, Grinblatt and Nozawa (2025)</a> Bond Returns (continued)				
High–Middle	–0.63 [–4.21]	–0.62 [–4.23]	–0.47 [–3.16]	–0.46 [–3.10]
High–Low	–0.72 [–4.88]	–0.72 [–4.87]	–0.61 [–4.23]	–0.61 [–4.15]
Alpha Factors	SB14	SB15	SB14	SB15
Panel C: Firm-Level Loan Return				
Panel C.1: Month-End to Month-End Loan Returns (Mean Monthly # Per Portfolio: 33)				
Middle–Low	–0.04 [–1.28]	–0.04 [–1.54]	–0.03 [–1.00]	–0.04 [–1.35]
High–Middle	–0.22 [–1.95]	–0.24 [–2.03]	–0.21 [–1.93]	–0.22 [–1.93]
High–Low	–0.26 [–2.10]	–0.28 [–2.23]	–0.25 [–2.11]	–0.26 [–2.17]
Panel C.2: <a href="#">Bartram, Grinblatt and Nozawa (2025)</a> Loan Returns (Mean Monthly # Per Portfolio: 38)				
Middle–Low	–0.07 [–1.68]	–0.08 [–1.89]	–0.03 [–0.91]	–0.04 [–1.38]
High–Middle	–0.16 [–2.28]	–0.17 [–2.33]	–0.18 [–2.15]	–0.19 [–2.17]
High–Low	–0.23 [–2.50]	–0.25 [–2.63]	–0.22 [–2.24]	–0.23 [–2.35]
Alpha Factors	SB14	SB15	SB14	SB15
Panel D: Firm-Asset Returns				
Panel D.1: Month-End to Month-End Firm-Asset Returns (Mean Monthly # Per Portfolio: 33)				
Middle–Low	0.07 [0.41]	0.09 [0.52]	0.20 [1.91]	0.20 [1.91]
High–Middle	–0.74 [–3.55]	–0.74 [–3.46]	–0.80 [–4.88]	–0.80 [–4.87]
High–Low	–0.67 [–2.36]	–0.65 [–2.31]	–0.60 [–3.31]	–0.60 [–3.31]
Panel D.2: <a href="#">Bartram, Grinblatt and Nozawa (2025)</a> Firm-Asset Returns (Mean Monthly # Per Portfolio: 38)				
Middle–Low	0.02 [0.18]	0.02 [0.17]	0.16 [1.70]	0.14 [1.51]
High–Middle	–0.50 [–2.81]	–0.50 [–2.76]	–0.62 [–4.49]	–0.63 [–4.44]
High–Low	–0.47 [–2.06]	–0.48 [–2.02]	–0.46 [–2.90]	–0.48 [–2.89]
Alpha Factors	SB17	SB18	SB17	SB18

**Table IA.12: Stock, Bond, Loan, and Asset Regressions on Distress Risk: Transaction-Price Subsample**

The table offers the results from [Fama and MacBeth \(1973\)](#) regressions of the excess returns of stocks, firm-specific bond portfolios, firm-specific loan portfolios, and firm-specific asset portfolios over month  $t$  on two distress dummy variables and controls at the end of month  $t - 1$  in the stock-bond-loan-asset sample exclusively using TRACE transaction prices to calculate bond returns and controlling for illiquidity and liquidity risk in columns (3) and (5). We create the bond (loan) [firm asset] portfolios by forming value-weighted portfolios of all outstanding bonds (loans) [firm assets] by firm. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if [Campbell et al. \(2008\)](#) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls also used in the main paper. Bond illiquidity is a bond's daily-price-change autocovariance (see [Bao et al. \(2011\)](#)), while its liquidity beta is its loading on the orthogonalized aggregate signed volume coefficient obtained from first-stage regressions (see [Lin et al. \(2011\)](#)). Plain numbers are monthly premium estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics calculated with a twelve-month lag length. The columns labelled "ME-ME" ("BGN") rely on standard ([Bartram et al. \(2025; BGN\)](#)) returns.

	Stocks with Loans	Bonds with Stocks & Loans	Bonds with Stocks & Loans	Bonds with Stocks & Loans	Loans with Stocks	Firm Assets with Stocks & Loans			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>HighDistress</i>	-1.07 [-2.33]	-0.82 [-2.66]	-0.97 [-2.56]	-0.43 [-1.85]	-0.47 [-1.92]	-0.33 [-1.78]	-0.16 [-1.58]	-0.87 [-4.18]	-0.45 [-1.97]
<i>LowDistress</i>	0.14 [0.39]	0.19 [2.04]	0.24 [2.29]	0.25 [1.90]	0.26 [2.03]	0.02 [0.34]	0.04 [0.65]	0.14 [0.92]	0.16 [1.40]
<i>MarketBeta</i>	0.33 [1.24]	0.00 [0.01]	-0.03 [-0.28]	0.06 [0.57]	0.05 [0.62]	0.04 [0.52]	0.04 [0.66]	0.09 [0.65]	0.10 [0.77]
<i>MarketSize</i>	-0.13 [-1.60]	-0.14 [-2.20]	-0.13 [-2.11]	-0.15 [-2.07]	-0.11 [-1.77]	0.01 [0.67]	0.00 [0.32]	-0.04 [-0.95]	-0.03 [-0.78]
<i>BookToMarket</i>	-0.20 [-1.55]	-0.08 [-1.39]	-0.06 [-1.21]	-0.07 [-1.46]	-0.07 [-1.72]	0.01 [0.18]	-0.01 [-0.30]	-0.11 [-1.74]	-0.13 [-2.32]
<i>Momentum</i>	-0.05 [-0.10]	0.07 [0.30]	-0.01 [-0.06]	0.12 [0.53]	0.10 [0.51]	0.19 [1.85]	0.14 [1.70]	0.06 [0.26]	0.14 [0.66]
<i>AssetGrowth</i>	-0.45 [-1.00]	-0.02 [-0.14]	0.00 [0.01]	-0.10 [-0.62]	0.01 [0.05]	-0.08 [-0.94]	-0.04 [-0.72]	-0.07 [-0.42]	0.06 [0.38]
<i>Profitability</i>	-0.52 [-0.85]	-0.41 [-1.05]	-0.36 [-1.05]	-0.37 [-1.07]	-0.33 [-0.89]	0.24 [1.96]	0.19 [1.53]	-0.49 [-1.20]	-0.42 [-1.00]
<i>BondMarketBeta</i>		1.61 [1.52]	1.34 [2.10]	1.00 [1.02]	0.95 [1.53]				
<i>BondSize</i>		0.02 [0.41]	0.01 [0.20]	0.01 [0.17]	0.00 [-0.04]				
<i>BondMaturity</i>		0.19 [1.21]	0.34 [1.97]	0.20 [1.58]	0.24 [1.93]				
<i>BondCreditRating</i>		0.04 [0.28]	0.07 [0.69]	0.15 [1.09]	0.20 [1.65]				

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<i>BondDownsideRisk</i>	-2.56	-1.85	-1.88	0.11					
	[-0.91]	[-0.94]	[-0.60]	[0.05]					
<i>BondReversal</i>	-12.87	-15.03	-13.72	-14.84					
	[-4.41]	[-4.97]	[-4.52]	[-4.83]					
<i>BondIlliquidity</i>		-0.04		-0.09					
		[-0.68]		[-1.98]					
<i>BondLiquidityBeta</i>		0.18		0.04					
		[0.62]		[0.16]					
<i>LoanSize</i>	-0.02	-0.01	0.03	0.04	-0.04	-0.01	-0.10	-0.08	
	[-0.55]	[-0.24]	[0.59]	[0.89]	[-2.19]	[-0.55]	[-1.60]	[-1.27]	
<i>LoanMaturity</i>	0.06	0.07	-0.04	-0.04	-0.03	0.01	-0.06	-0.13	
	[0.50]	[0.57]	[-0.31]	[-0.43]	[-0.38]	[0.14]	[-0.61]	[-1.52]	
Return Type	ME-ME	ME-ME	ME-ME	BGN	BGN	ME-ME	BGN	ME-ME	BGN

**Table IA.13: Bond Distress Portfolios: M&A Adjustment**

The table offers the SB14 alphas of bond portfolios univariately sorted on distress risk in the stock-bond sample reassigning surviving bonds to acquiring firms after a merger-and-acquisition (M&A) deal. While columns (1) and (3) focus on standard returns, columns (2) and (4) concentrate on [Bartram et al. \(2025\)](#) BGN returns, respectively. We sort our sample firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm) into portfolios according to the decile breakpoints of [Campbell et al. \(2008\)](#) distress risk at the end of month  $t - 1$ . We value (columns (1) and (2)) or equally ((3) and (4)) weight the portfolios and hold them over month  $t$ , where we use a firm’s total bond capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the fifth (top) [top] decile portfolio and short the bottom (fifth) [bottom] (“Middle–Low” (“High–Middle”) [“High–Low”]). SB14 indicates the 14-factor stock-bond model. Plain numbers are monthly estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

	Value-Weighted Portfolios		Equally-Weighted Portfolios	
	St. Return Monthly Alpha	BGN Return Monthly Alpha	St. Return Monthly Alpha	BGN Return Monthly Alpha
	(1)	(2)	(3)	(4)
Medium–Low	–0.06 [–2.05]	–0.07 [–2.26]	–0.07 [–2.99]	–0.07 [–3.18]
High–Middle	–0.41 [–6.24]	–0.41 [–6.20]	–0.35 [–6.36]	–0.34 [–6.31]
High–Low	–0.47 [–7.66]	–0.47 [–7.72]	–0.42 [–7.29]	–0.41 [–7.22]
Alpha Factors	SB14	SB14	SB14	SB14

**Table IA.14: Bond Regressions on Distress Risk: M&A Adjustment**

The table offers the results from [Fama and MacBeth \(1973\)](#) regressions of the excess returns of all, investment-grade (IG), and speculative-grade (SG) firm-specific bond portfolios over month  $t$  on two distress dummy variables and controls at the end of month  $t - 1$  in the stock-bond sample reassigning surviving bonds to acquiring firms after a merger-and-acquisition (M&A) deal. We create the bond portfolios by forming value-weighted portfolios of all outstanding bonds by firm. Investment (speculative) grade bonds have a rating equal to or above (below) BBB- at the end of month  $t - 1$ . The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if [Campbell et al. \(2008\)](#) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. See [Table A1](#) in [Appendix A](#) at the end of the main paper for details about the controls. Plain numbers are monthly premium estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics calculated with a twelve-month lag length. The columns labelled “ME-ME” (“BGN”) rely on standard ([Bartram et al. \(2025\)](#); BGN) returns.

	All Bonds	All Bonds	IG Bonds	IG Bonds	SG Bonds	SG Bonds
	(1)	(2)	(3)	(4)	(5)	(6)
<i>HighDistress</i>	-0.26 [-4.67]	-0.25 [-4.64]	-0.12 [-3.81]	-0.11 [-3.47]	-0.42 [-4.90]	-0.41 [-4.93]
<i>LowDistress</i>	0.06 [4.23]	0.05 [3.87]	0.04 [3.84]	0.04 [3.86]	0.10 [2.23]	0.09 [2.07]
<i>MarketBeta</i>	0.05 [2.24]	0.05 [2.22]	0.01 [0.77]	0.01 [0.65]	0.05 [1.07]	0.06 [1.21]
<i>MarketSize</i>	-0.03 [-3.54]	-0.03 [-3.53]	-0.01 [-1.61]	-0.01 [-1.54]	-0.05 [-2.21]	-0.05 [-2.24]
<i>BookToMarket</i>	0.00 [-0.25]	0.00 [-0.22]	-0.01 [-1.21]	-0.01 [-1.11]	0.00 [-0.07]	0.00 [-0.05]
<i>Momentum</i>	0.08 [1.75]	0.08 [1.75]	0.13 [3.50]	0.13 [3.57]	-0.11 [-1.01]	-0.12 [-1.07]
<i>AssetGrowth</i>	0.05 [1.30]	0.05 [1.46]	0.02 [0.79]	0.03 [1.03]	-0.06 [-0.76]	-0.06 [-0.82]
<i>Profitability</i>	0.01 [0.32]	0.00 [0.07]	-0.03 [-1.13]	-0.04 [-1.39]	-0.03 [-0.23]	-0.05 [-0.36]
<i>BondMarketBeta</i>	0.11 [1.12]	0.09 [0.99]	-0.09 [-0.78]	-0.12 [-0.87]	0.24 [1.50]	0.25 [1.58]
<i>BondSize</i>	-0.03 [-1.44]	-0.04 [-2.18]	-0.03 [-1.93]	-0.05 [-2.80]	-0.02 [-0.51]	-0.03 [-0.61]
<i>BondMaturity</i>	0.08 [2.37]	0.07 [2.38]	0.08 [2.49]	0.07 [2.46]	0.06 [1.06]	0.07 [1.22]
<i>BondCreditRating</i>	0.11 [2.69]	0.10 [2.53]	0.07 [2.39]	0.05 [1.83]	0.24 [1.24]	0.23 [1.18]
<i>BondDownsideRisk</i>	3.77 [4.41]	3.79 [4.44]	2.51 [3.08]	2.67 [3.22]	2.17 [1.50]	2.02 [1.41]
<i>BondReversal</i>	-9.77 [-5.45]	-9.79 [-5.54]	-9.08 [-5.61]	-8.98 [-5.60]	-7.61 [-3.86]	-7.73 [-3.95]
Return Type	ME-ME	BGN	ME-ME	BGN	ME-ME	BGN

**Table IA.15: Bond, Loan, & Asset Distress Portfolios: M&A Adjustment**

The table offers the monthly alphas of bond, loan, and firm-asset portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample reassigning surviving bonds and loans to acquiring firms after a merger-and-acquisition (M&A) deal. Panels A and B focus on standard and Bartram et al. (2025; BGN) bond returns, respectively. We sort our sample firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm), firm-specific loan portfolios (i.e., the value-weighted portfolios of all outstanding loans by firm), and firm-specific asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month  $t - 1$ . We value (columns (1) to (3)) or equally ((4) to (6)) weight the portfolios and hold them over month  $t$ , where we use a firm's total bond, loan, and firm-asset capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] (“Middle–Low” (“High–Middle”) [“High–Low”]). SB14 and SB17 indicate the 14 and 17-factor stock-bond model, respectively. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987)  $t$ -statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

	Value-Weighted Portfolios			Equally-Weighted Portfolios		
	Bond Monthly Alpha	Loan Monthly Alpha	Firm-Asset Monthly Alpha	Bond Monthly Alpha	Loan Monthly Alpha	Firm-Asset Monthly Alpha
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Month-End to Month-End Returns						
Medium–Low	0.00 [−0.04]	−0.03 [−0.88]	0.21 [0.92]	−0.09 [−1.24]	−0.03 [−1.08]	0.36 [1.98]
High–Middle	−0.85 [−3.83]	−0.34 [−3.06]	−0.88 [−3.49]	−0.65 [−3.12]	−0.33 [−3.12]	−0.85 [−4.56]
High–Low	−0.85 [−3.80]	−0.37 [−3.05]	−0.67 [−2.49]	−0.74 [−3.70]	−0.36 [−3.27]	−0.50 [−2.73]
Panel B: Bartram, Grinblatt and Nozawa (2025) Returns						
Medium–Low	−0.05 [−0.78]	−0.06 [−1.50]	0.31 [1.28]	−0.10 [−1.47]	0.00 [−0.07]	0.40 [2.32]
High–Middle	−0.88 [−4.20]	−0.27 [−2.88]	−0.87 [−3.39]	−0.70 [−3.65]	−0.30 [−3.35]	−0.82 [−4.68]
High–Low	−0.93 [−4.27]	−0.32 [−3.21]	−0.56 [−2.47]	−0.80 [−4.15]	−0.30 [−3.21]	−0.42 [−2.77]
Alpha Factors	SB14	SB14	SB17	SB14	SB14	SB17

**Table IA.16: Bond, Loan, & Asset Regressions on Distress Risk: M&A Adjustment**

The table offers the results from Fama and MacBeth (1973) regressions of the excess returns of firm-specific bond portfolios, firm-specific loan portfolios, and firm-specific asset portfolios over month  $t$  on two distress dummy variables and controls at the end of month  $t - 1$  in the stock-bond-loan-asset sample reassigning surviving bonds and loans to acquiring firms after a merger-and-acquisition (M&A) deal. We create the bond (loan) [firm asset] portfolios by forming value-weighted portfolios of all outstanding bonds (loans) [firm assets] by firm. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if Campbell et al. (2008) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls. Plain numbers are monthly premium estimates (in %), while those in square parentheses are Newey and West (1987)  $t$ -statistics calculated with a twelve-month lag length. The columns labelled “ME-ME” (“BGN”) rely on standard (Bartram et al. (2025; BGN)) returns.

	Bonds with Stocks & Loans		Loans with Stocks		Firm Assets with Stocks & Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>HighDistress</i>	-0.84 [-2.87]	-0.98 [-3.38]	-0.54 [-2.82]	-0.42 [-3.22]	-0.76 [-2.98]	-0.86 [-3.08]
<i>LowDistress</i>	0.21 [2.39]	0.09 [0.72]	0.01 [0.25]	-0.01 [-0.18]	0.03 [0.29]	-0.06 [-0.45]
<i>MarketBeta</i>	-0.03 [-0.36]	-0.01 [-0.15]	-0.01 [-0.13]	0.00 [-0.01]	0.01 [0.05]	-0.08 [-0.58]
<i>MarketSize</i>	-0.11 [-2.71]	-0.15 [-3.03]	0.00 [-0.09]	-0.01 [-0.56]	-0.08 [-1.74]	-0.08 [-1.82]
<i>BookToMarket</i>	0.01 [0.26]	0.05 [0.77]	0.00 [-0.13]	-0.03 [-1.26]	-0.03 [-0.37]	-0.07 [-1.08]
<i>Momentum</i>	0.06 [0.28]	0.19 [0.95]	0.19 [2.11]	0.18 [2.22]	0.21 [0.88]	0.39 [1.59]
<i>AssetGrowth</i>	0.07 [0.48]	-0.03 [-0.21]	-0.04 [-0.59]	-0.02 [-0.45]	-0.09 [-0.67]	-0.12 [-0.98]
<i>Profitability</i>	-0.19 [-0.72]	0.02 [0.10]	0.21 [1.66]	0.23 [1.89]	0.02 [0.05]	0.02 [0.06]
<i>BondMarketBeta</i>	0.89 [1.05]	1.18 [1.34]				
<i>BondSize</i>	0.02 [0.61]	0.01 [0.16]				
<i>BondMaturity</i>	0.19 [2.01]	0.25 [1.92]				
<i>BondCreditRating</i>	0.34 [2.42]	0.34 [2.58]				
<i>BondDownsideRisk</i>	-0.88 [-0.33]	-2.87 [-0.85]				
<i>BondReversal</i>	-8.70 [-2.73]	-9.58 [-3.06]				

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<i>LoanSize</i>	-0.04 [-0.89]	-0.05 [-1.04]	-0.02 [-0.94]	0.00 [0.11]	-0.09 [-1.72]	-0.07 [-1.35]
<i>LoanMaturity</i>	0.05 [0.60]	-0.19 [-0.90]	-0.08 [-1.24]	-0.02 [-0.39]	-0.03 [-0.32]	-0.10 [-1.08]
Return Type	ME-ME	BGN	ME-ME	BGN	ME-ME	BGN

**Table IA.17: The Equity and Liability Structure of Our Sample Firms**

The table offers descriptive statistics on the proportions of current liabilities (first subpanel), long-term liabilities (second subpanel), and equities (third subpanel) of the firms in Compustat (Panel A) and the stock-bond-loan-asset subsample (Panel B) over the 1999 to 2020 sample period. The descriptive statistics include the number of observations, the mean, the standard deviation (St. Dev.), and the fifth, 25th, 50th, 75th, and 95th percentile, first calculated by fiscal year and then averaged over time. The current liabilities are accounts payable, debt in current liabilities, income taxes payable, and other. We also report the share of other attributable to accrued expenses, if available. The long-term liabilities are long-term debt, deferred taxes and investment tax credits, non-controlling interests, and other. We also report the share of long-term debt attributable to capitalized leases. The equities are common and preferred equity.

	Obs.	Mean	St.	Percentiles				
			Dev.	5	25	50	75	95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample (1999-2020)								
Panel A.1: Current Liabilities								
Accounts Payable	4,775	0.08	0.09	0.00	0.02	0.05	0.10	0.26
Debt in Current Liabilities	4,775	0.06	0.12	0.00	0.00	0.01	0.05	0.31
Income Taxes Payable	4,775	0.00	0.01	0.00	0.00	0.00	0.00	0.02
Other	4,775	0.12	0.12	0.00	0.04	0.09	0.16	0.37
- Accrued Expenses	3,905	0.07	0.07	0.00	0.03	0.05	0.09	0.19
Panel A.2: Long-Term Liabilities								
Long-Term Debt	4,775	0.15	0.21	0.00	0.00	0.04	0.25	0.61
- Capitalized Leases	4,775	0.00	0.02	0.00	0.00	0.00	0.00	0.02
Def. Taxes and Inv. Tax Credits	4,775	0.01	0.03	0.00	0.00	0.00	0.01	0.08
Noncontrolling Interests	4,775	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other	4,775	0.05	0.09	0.00	0.00	0.01	0.05	0.19
Panel A.3: Equity								
Common Equity	4,775	0.49	0.28	0.01	0.27	0.51	0.73	0.92
Preferred Equity	4,775	0.03	0.13	0.00	0.00	0.00	0.00	0.19
Panel B: Firm-Asset Sample (1999-2020)								
Panel B.1: Current Liabilities								
Accounts Payable	151	0.06	0.06	0.01	0.02	0.04	0.09	0.18
Debt in Current Liabilities	151	0.02	0.06	0.00	0.00	0.01	0.02	0.08
Income Taxes Payable	151	0.00	0.01	0.00	0.00	0.00	0.01	0.02
Other	151	0.09	0.07	0.02	0.05	0.07	0.11	0.21
- Accrued Expenses	136	0.06	0.04	0.01	0.03	0.05	0.07	0.13

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Panel B.2: Long-Term Liabilities								
Long-Term Debt	151	0.43	0.22	0.04	0.28	0.42	0.59	0.79
- Capitalized Leases	151	0.01	0.02	0.00	0.00	0.00	0.00	0.03
Def. Taxes and Inv. Tax Credits	151	0.03	0.04	0.00	0.00	0.02	0.06	0.12
Noncontrolling Interests	151	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Other	151	0.06	0.07	0.00	0.01	0.03	0.08	0.18
Panel B.3: Equity								
Common Equity	151	0.28	0.20	0.00	0.12	0.28	0.42	0.64
Preferred Equity	151	0.01	0.06	0.00	0.00	0.00	0.00	0.07

**Table IA.18: The Debt Structure of Our Sample Firms**

The table offers descriptive statistics on the proportions of debt instruments of the firms in Compustat (Panel A) and the stock-bond-loan-asset subsample (Panel B) over the 1999 to 2020 sample period. The descriptive statistics include the number of observations, the mean, the standard deviation (St. Dev.), and the fifth, 25th, 50th, 75th, and 95th percentile, first calculated by fiscal year and then averaged over time. The debt instruments are commercial paper, revolving credit lines, term loans, senior bonds, subordinated bonds, capital leases, trust preferred funds, general other borrowing, and the residual adjustment. The residual adjustment is calculated by Capital IQ to ensure that the proportions sum up to 100%.

	Obs.	Mean	St. Dev.	Percentiles				
	(1)	(2)	(3)	5	25	50	75	95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample (1999-2020)								
Commercial Paper	5,923	0.01	0.04	0.00	0.00	0.00	0.00	0.01
Revolving Credit Lines	5,923	0.16	0.29	0.00	0.00	0.01	0.15	0.97
Term Loans	5,923	0.27	0.36	0.00	0.00	0.02	0.53	0.98
Senior Bonds	5,923	0.36	0.41	0.00	0.00	0.11	0.77	1.00
Subordinated Bonds	5,923	0.05	0.16	0.00	0.00	0.00	0.02	0.33
Capital Leases	5,923	0.06	0.19	0.00	0.00	0.00	0.02	0.35
Trust Preferred Funds	5,923	0.01	0.07	0.00	0.00	0.00	0.00	0.06
General Other Borrowing	5,923	0.09	0.24	0.00	0.00	0.00	0.01	0.80
Residual Adjustment	5,923	-0.01	0.08	-0.06	0.00	0.00	0.00	0.03
Panel B: Firm-Asset Sample (1999-2020)								
Commercial Paper	211	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Revolving Credit Lines	211	0.09	0.18	0.00	0.00	0.02	0.09	0.50
Term Loans	211	0.43	0.35	0.00	0.10	0.39	0.74	0.98
Senior Bonds	211	0.32	0.33	0.00	0.00	0.20	0.58	0.94
Subordinated Bonds	211	0.09	0.16	0.00	0.00	0.01	0.14	0.41
Capital Leases	211	0.03	0.08	0.00	0.00	0.00	0.02	0.11
Trust Preferred Funds	211	0.00	0.02	0.00	0.00	0.00	0.00	0.02
General Other Borrowing	211	0.04	0.14	0.00	0.00	0.00	0.01	0.29
Residual Adjustment	211	0.00	0.05	-0.03	-0.01	0.00	0.00	0.02

**Table IA.19: Asset Distress Portfolios: Alternative Firm-Asset Returns**

The table offers the SB17 alphas of firm-asset portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample based on alternative firm-asset returns. Panels A and B focus on standard and [Bartram et al. \(2025; BGN\)](#) returns, respectively. Columns (1) and (5) rely on our original asset returns also used in our main tests, columns (2) and (6) on asset returns including trade credit as fourth asset class, columns (3) and (7) on asset returns exploiting Capital IQ data to adjust the asset-class weights, and columns (4) and (8) on asset returns exploiting Compustat and Mergent FISD data to adjust the asset-class weights. We sort our sample firm-specific asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of [Campbell et al. \(2008\)](#) distress risk at the end of month  $t - 1$ . We value (columns (1) to (4)) or equally ((5) to (8)) weight the portfolios and hold them over month  $t$ , where we use a firm’s total asset capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] (“Middle–Low” (“High–Middle”) [“High–Low”]). SB17 indicates the 17-factor stock-bond model. Plain numbers are monthly estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

	Value-Weighted Portfolios				Equally-Weighted Portfolios			
	Trade Credit Original Returns	Loan Weight Adjusted Returns	Bond-Loan Weight Adjusted Returns		Trade Credit Original Returns	Loan Weight Adjusted Returns	Bond-Loan Weight Adjusted Returns	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Month-End to Month-End Firm-Asset Returns								
Middle–Low	0.14 [0.62]	0.23 [1.30]	0.11 [0.50]	0.21 [1.23]	0.31 [1.77]	0.32 [2.35]	0.29 [1.60]	0.33 [1.80]
High–Middle	–0.80 [–3.41]	–0.77 [–3.79]	–0.75 [–3.29]	–0.77 [–3.00]	–0.83 [–4.46]	–0.76 [–4.82]	–0.82 [–4.51]	–0.74 [–3.43]
High–Low	–0.66 [–2.71]	–0.54 [–2.63]	–0.63 [–2.76]	–0.56 [–2.71]	–0.52 [–2.88]	–0.44 [–2.76]	–0.53 [–2.94]	–0.42 [–2.58]
Panel B: <a href="#">Bartram, Grinblatt and Nozawa (2025)</a> Firm-Asset Returns								
Middle–Low	0.23 [1.09]	0.29 [1.68]	0.19 [0.94]	0.21 [1.54]	0.38 [2.45]	0.37 [3.02]	0.37 [2.35]	0.36 [2.33]
High–Middle	–0.73 [–3.15]	–0.70 [–3.42]	–0.67 [–2.98]	–0.59 [–2.85]	–0.76 [–4.78]	–0.69 [–5.14]	–0.73 [–4.72]	–0.65 [–3.68]
High–Low	–0.50 [–2.63]	–0.42 [–2.64]	–0.47 [–2.69]	–0.37 [–2.38]	–0.38 [–2.52]	–0.32 [–2.42]	–0.37 [–2.40]	–0.29 [–2.19]
Alphas	SB17	SB17	SB17	SB17	SB17	SB17	SB17	SB17

**Table IA.20: Firm-Asset Regressions on Distress Risk: Alternative Firm-Asset Returns**

The table offers the results from [Fama and MacBeth \(1973\)](#) regressions of the excess returns of firm assets over month  $t$  on two distress dummy variables and controls at the end of month  $t - 1$  in the stock-bond-loan-asset sample based on alternative firm-asset returns. Columns (1) and (2) rely on our original asset returns also used in our main tests, columns (3) and (4) on asset returns including trade credit as fourth asset class, columns (5) and (6) on asset returns exploiting Capital IQ data to adjust the asset-class weights, and columns (7) and (8) on asset returns exploiting Compustat and Mergent FISD data to adjust the asset-class weights. We create the firm asset portfolios by forming value-weighted portfolios of all firm assets by firm. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if [Campbell et al. \(2008\)](#) distress risk is within the top decile (below the median) at the end of month  $t - 1$  and else zero. See [Table A1](#) in [Appendix A](#) at the end of the main paper for details about the controls. Plain numbers are monthly premium estimates (in %), while those in square parentheses are [Newey and West \(1987\)](#)  $t$ -statistics calculated with a twelve-month lag length. The columns labelled “ME-ME” (“BGN”) rely on standard ([Bartram et al. \(2025\)](#); BGN) returns.

	Original Asset Returns (for comparison)		Trade Credit Adjusted Asset Returns		Loan Weight Adjusted Asset Returns		Bond + Loan Weight Adjusted Asset Returns	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>HighDistress</i>	-0.79 [-3.21]	-0.75 [-3.09]	-0.65 [-3.31]	-0.63 [-3.13]	-0.80 [-3.36]	-0.68 [-3.47]	-0.54 [-2.56]	-0.47 [-2.33]
<i>LowDistress</i>	0.02 [0.12]	0.00 [-0.00]	0.01 [0.11]	-0.01 [-0.08]	-0.03 [-0.22]	-0.04 [-0.32]	0.09 [0.86]	0.04 [0.34]
<i>MarketBeta</i>	0.01 [0.05]	-0.08 [-0.52]	-0.04 [-0.32]	-0.11 [-0.80]	-0.01 [-0.11]	-0.12 [-0.72]	-0.05 [-0.45]	-0.16 [-1.19]
<i>MarketSize</i>	-0.06 [-1.54]	-0.07 [-1.66]	-0.07 [-1.83]	-0.08 [-1.96]	-0.04 [-0.90]	-0.05 [-1.23]	-0.04 [-1.05]	-0.05 [-1.31]
<i>BookToMarket</i>	-0.03 [-0.37]	-0.13 [-1.40]	-0.04 [-0.68]	-0.13 [-1.60]	-0.02 [-0.29]	-0.12 [-1.34]	0.05 [0.57]	0.01 [0.15]
<i>Momentum</i>	0.23 [0.96]	0.39 [1.69]	0.23 [1.10]	0.39 [1.89]	0.22 [0.92]	0.40 [1.75]	0.12 [0.49]	0.16 [0.66]
<i>AssetGrowth</i>	-0.02 [-0.15]	-0.02 [-0.16]	0.01 [0.09]	-0.01 [-0.05]	-0.07 [-0.44]	-0.07 [-0.53]	0.09 [0.76]	0.05 [0.45]
<i>Profitability</i>	0.07 [0.17]	0.32 [0.69]	0.00 [0.01]	0.23 [0.59]	0.15 [0.34]	0.39 [0.82]	0.13 [0.46]	0.28 [0.90]
<i>LoanSize</i>	-0.09 [-1.50]	-0.05 [-0.85]	-0.08 [-1.55]	-0.04 [-0.74]	-0.10 [-1.66]	-0.06 [-1.16]	-0.10 [-2.35]	-0.05 [-0.99]
<i>LoanMaturity</i>	-0.06 [-0.60]	-0.15 [-1.53]	0.00 [-0.01]	-0.09 [-1.10]	-0.05 [-0.51]	-0.11 [-1.15]	0.03 [0.49]	-0.02 [-0.28]
Return Type	ME-ME	BGN	ME-ME	BGN	ME-ME	BGN	ME-ME	BGN