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BOOK-TO-MARKET, MISPRICING, AND THE CROSS-SECTION OF CORPORATE BOND RETURNS

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Abstract

A corporate bond's book value divided by its market price predicts its return from actual transactions occurring at least eight days after signal observation. Senior bonds with the 20% highest "bond book-to-market ratios" outperform their lowest-quintile counterparts by at least 3–4% per year, even for subsamples restricted to investment-grade ratings. The universe of all bonds exhibits even larger spreads. These findings control for liquidity, default, market microstructure, and priced asset risk inferred from yields, credit spreads, bid-ask spreads, structural model equity hedges, duration, bond ratings, industry, maturity, and coupons. Efficient markets stories cannot explain the spread, particularly in light of the substantial decay in alpha when implementation is delayed, the negligible role of credit risk and liquidity in signal efficacy, the degree to which return spreads exceed yield spreads, and the significant spreads left after accounting for factor risk, including a bond-specific "value factor." We also rule out off-market pricing provided by central dealers or provided to favored customers.

JEL Classification: G11, G12, G14

Keywords: Corporate bonds, Market efficiency, Credit risk, Transaction costs, Point-in-time (pit), Book-to-market

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and the Cross-Section of Corporate Bond Returns

Abstract

A corporate bond's book value divided by its market price predicts its return from actual transactions occurring at least eight days after signal observation. Senior bonds with the 20% highest "bond book-to-market ratios" outperform their lowest-quintile counterparts by at least 3–4% per year, even for subsamples restricted to investment-grade ratings. The universe of all bonds exhibits even larger spreads. These findings control for liquidity, default, market microstructure, and priced asset risk inferred from yields, credit spreads, bid-ask spreads, structural model equity hedges, duration, bond ratings, industry, maturity, and coupons. Efficient markets stories cannot explain the spread, particularly in light of the substantial decay in alpha when implementation is delayed, the negligible role of credit risk and liquidity in signal efficacy, the degree to which return spreads exceed yield spreads, and the significant spreads left after accounting for factor risk, including a bond-specific "value factor." We also rule out off-market pricing provided by central dealers or provided to favored customers.

Keywords: Credit Risk, Corporate Bonds, Book-to-Market, Market Efficiency, Transaction Costs, Point-in-Time
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Research spanning three decades features "book-to-market" as a key driver of the cross-section of equity returns. One theory explaining its prominent role is that book-to-market proxies for priced risk. For example, Berk (1995) points out that high risk firms discount future cash flows at higher rates, implying that high risk firms should exhibit both low market prices and high book-to-market ratios, other things equal. Thus, whenever alpha measurement imperfectly controls for risk, book-to-market will proxy for omitted risk factors and spuriously generate alpha. An equally plausible alternative is that, on average, high book-to-market ratios reflect underpriced shares, and low ratios reflect overpriced shares. This interpretation of book-to-market as a mispricing metric views book equity as a crude measure of equity fair value. Here, high book-to-market firms' high equity returns express rates that translate excessively low prices into future payoffs. If pricing mistakes rather than omitted risk factors account for book-to-market's relation with returns, alpha's correlation with book-to-market warrants active trading that exploits valuation errors.

Because equities lack accurate models of risk premia, assessing whether risk or mispricing explains book-to-market's return correlation is a heroic task. By contrast, with corporate bonds, which we show exhibit a similar book-to-market correlation, assessment of the competing theories is far simpler. For one, fair prices for bonds are easier to infer than for equities. Indeed, bond dealers typically derive quotes and marks for bonds with "matrix pricing"—in which a bond's fair price is a time varying function of many bond characteristics that influence other bonds' prices. Matrix pricing of a bond's fair value is only possible because the magnitude and timing of future cash flows are more transparent for bonds than for equities. The future cash flows of many bonds are also known with relative certainty; for the senior bonds we focus on, only extreme and infrequent outcomes for the economy or a company materially affect the likelihood of meeting payment promises. Discount rate variation thus has far more influence over these bonds' monthly returns than changes in cash flow projections, facilitating risk measurement compared to equities.

To this end, we define the "bond book-to-market ratio" ("BBM") as the bond's book value divided by its market price, which positively predicts a bond's return. (Book value, an amortizing issue price, linearly converges to the bond's face value at maturity.) BBM's 5% per year extreme-quintile return spread is almost as large as equity's familiar book-to-market spread and exhibits a greater Sharpe ratio (0.9). It is also far larger than the quintiles' yield spread from bonds' *promised* payments, even for investment-grade bonds. Indeed, credit risk, which we control for, has little impact on BBM signal efficacy. Abundant controls make it difficult to entertain risk mismeasurement as the source of BBM's significant raw and risk-adjusted spreads. Nor can a risk story explain why the equity-hedged bond returns implicit in corporate bond structural models exhibit a BBM anomaly of the same magnitude as unhedged bond returns; or why inclusion of a bond equivalent of Fama and French's (1993) equity book-to-market factor, HML, leaves a significant alpha in time series regressions of returns from a BBM long-short trading strategy on factor risk.

Tax and liquidity differences do not explain the anomaly either: high-BBM bonds tend to be taxed less and traded more than their low-BBM counterparts. Moreover, their round-trip institutional trading costs are about the same (5 bp higher for the highest BBM quintile), while regressions employing a bond's bid-ask spread as a control show that bonds with high vs. low bid-ask spreads, trading volume, or numbers of trades—all measured *ex ante* to avoid bias—exhibit about the same degree of BBM return predictability.

BBM starts at one when a bond is issued. Most bonds' coupons are set so that a bond's book value at issue and face amount paid at maturity are approximately the same—referred to as a "par bond." Over time, the book-to-market ratios of formerly par bonds then rise above one (making them discount bonds) or fall below one (premium bonds). Likewise, bonds issued at discounts or premia evolve to have greater or lesser discounts and premia than their amortization schedules would indicate. As with par bond issues, changing economic forces or sentiment could generate price deviations from those schedules.

If BBM broadly proxies for omitted risk or liquidity controls, which are more stable than sentiment, BBM signals should predict returns when implemented with modest delay. Because delays of a month or two torpedo BBM signal efficacy, BBM's anomaly cannot stem from BBM serving as an omitted control for most bonds within BBM's extreme quintiles. BBM evolves too slowly to render a delayed BBM signal so ineffective if it played this role. Likewise, BBM cannot proxy for the omitted controls of a few bonds that exit BBM's extreme quintiles each month, thus altering their premia. In this case, their changing risk/liquidity premia, needed to account for delay's effect on alpha's magnitude, would be orders of magnitude too large with no delay and change too rapidly to qualify as time-varying bond risk/liquidity premia.

By contrast, if sentiment materially distorts a bond's price, the effect is unlikely to persist, as arbitrage and mean reversion in sentiment force convergence to fair value. Hence, sentiment-driven low BBM ratios tend to rise, making risk-adjusted returns abnormally low; sentiment-driven high BBM ratios tend to fall, making returns abnormally high. If sentiment-based price distortions apply to only a few of the extreme-quintile BBM bonds, those distortions must be large to account for the BBM effect. In this case, a persistent characteristic like BBM will likely influence returns only for a short period of time. Prices for the vast majority of BBM's extreme-quintile bonds have no reason to similarly converge if they were priced fairly to begin with. Such rationally priced bonds are merely caught up in the extreme quintiles' wide nets.

BBM's evolution parallels that of the bond's yield-to-maturity ("YTM"). At issuance, the YTM of the ubiquitous par bond matches its coupon rate. If the bond's subsequent return exceeds its initial YTM, BBM and YTM will fall, and vice versa. Neither BBM nor YTM directly map into an expected return. However, YTM, particularly when deployed as a function of dummy variables for YTM ranks, better captures expected returns than the cruder BBM. Nevertheless, when controlling for YTM ranks, along with a host of other variables, including past returns, duration, credit spread, liquidity, and default likelihood, the highest BBM bond quintile outperforms the lowest by 3–4% per year.

The study of corporate bonds has heretofore been hindered by their thin trading, which makes it difficult to use transaction prices to measure monthly returns and strategy performance. We employ transaction prices from the relatively comprehensive TRACE database. Prior studies employing TRACE focus mostly on its most liquid bonds.[1] Constructing monthly returns for bonds that trade nearly every day, often multiple times, is straightforward. However, studies of such bonds cannot draw unbiased conclusions since liquidity could be correlated with bonds' returns or control variables. Filtering a sample ex-post for its most liquid bonds could lead to conclusions that do not even apply to the narrow set of bonds studied.

We construct monthly returns with an innovation that avoids the need for a liquidity filter. The innovation imputes monthly prices using the martingale property of fair risk-adjusted asset prices.[2] The martingale property implies that the first and last transaction price of each month can substitute as unbiased estimates of the numerator (end-of-month price) and denominator (beginning-of-month price) of each bond's monthly return calculation. If a bond's current yield (interest earned/price) matched its expected return, TRACE's "flat" price, i.e., bond price excluding accrued due, perfectly follows a martingale. In this case, the bond's imputed, unbiased beginning- and end-of-month flat prices generate noisy return estimates. These estimates, unlike their spreads, have a small upward bias due to Jensen's inequality.

When current yields do not fully reflect a bond's expected return, the flat price will not follow a martingale. For example, riskless bonds issued at par can become discount bonds, generating higher BBMs when interest rates increase and vice versa. Yet, both discount and premium riskless bonds have flat prices that converge to par at maturity. Such violations of the martingale property imply that our use of intra-month transactions to impute monthly prices and returns tends to understate high BBM bonds' full-month returns and overstate low BBM bonds' full-month returns. The same insight applies when market-wide credit spreads expand or shrink after issuance. Hence, the BBM return spread imputed with intra-month

[1] Such research typically applies filters that censor the sample or employ traders' models/quotes rather than transaction prices. Chordia et al. (2017) use a mix of dealer quotes and bonds in TRACE that trade in the last 5 trading days of the month. Bao et al. (2011) require a bond to trade on at least 75% of its relevant business days. Israel et al. (2018) select a monthly representative bond for each issuer based on seniority, maturity, age, and size. Schaefer and Strebulaev (2008) use prices contained in the most popular bond indices. Since bonds often do not trade for long periods, indices are partly built around mid-spread marks of traders' models that are divorced from nearby transactions.

[2] Note that the martingale property holds only under the null hypothesis of market efficiency. Behavioral-based return anomalies, the alternative hypothesis for which we present evidence, rejects efficiency. However, the alternative hypothesis is irrelevant for classical statistical tests and has no bearing on whether the martingale assumption is appropriate here.

prices conservatively estimates the true return spread for the full month. As a robustness check, we support this claim by demonstrating a BBM effect in end-of-month trader quotes on a limited set of liquid bonds.

Risk-adjusted profits from the BBM trading strategy with monthly rebalancing do not survive transaction costs, which are higher for corporate bonds than for stocks. Such costs may deter hedge funds and other short-term arbitrageurs from exploiting BBM, whether we estimate the costs from the prices of all trades between dealers and customers or only from trades with volumes exceeding 100,000 U.S. dollars. Nevertheless, a buy-and-hold variation of the strategy survives the transaction costs incurred by larger trades, enhancing overall net performance provided the institutions avoid additional short sales constraints and costs.[3] Merely tilting a long-only portfolio towards underpriced and away from overpriced bonds to some degree can avoid short sales and enhance performance given the size of the BBM effect observed.

A 50-year literature relates equity return anomalies to attributes.[4] In contrast to this abundant literature, research on similar issues in the bond market is sparse. For U.S. government bonds, research on informational efficiency includes Fama and Bliss (1987) and Cochrane and Piazzesi (2005), who show that forward rates predict returns, while Joslin et al. (2014) document that forward rates do not span risk premia. Cieslak and Povala (2015) enhance this return predictability by accounting for long-term inflation. In the cross-section, Asness et al. (2013) uncover value and momentum effects in government bond indices, while Brooks and Moskowitz (2017) find that value, momentum, and carry factors help predict government bond returns outside of the U.S. Finally, Brooks et al. (2020) show that exposure to traditional risk factors largely explains the active returns of fixed income managers.

Research on whether corporate bonds reflect public information and on corporate bond characteristics that account for the cross-section of corporate bond returns is nascent. Gebhardt et al. (2005) report that bonds with high default risk and distant maturities earn higher returns. Chordia et al. (2017), Jostova et al. (2013), Bai et al. (2019), and Bali et al. (2019) show that bond returns are correlated with past bond returns. Choi and Kim (2018), Israel et al. (2018), Avramov et al. (2019), and Bali et al. (2020) study factors and anomalies in bond markets, while Bretscher et al. (2020) resolve corporate finance puzzles with

[3] Asquith et al. (2013) show that the cost of shorting corporate bonds is comparable to that of stocks.

[4] Harvey et al. (2016) and Green et al. (2013) summarize over 300 return predictors, like earnings surprises (Ball and Brown, 1968), size (Banz, 1981), book-to-market (Fama and French, 1992), momentum (Jegadeesh and Titman, 1993), accruals (Sloan, 1996), cash-flow-to-price (Hou et al., 2011), earnings yield (Basu, 1983), and gross profitability (Novy-Marx, 2013). In addition, Fritzemeier (1936), Bachrach and Galai (1979), Basu (1978), Dubofsky and French (1988), and Lamont (1998) study price-related anomalies.

better estimates of firms' capital structures using debt market values. Labelling bond book-to-market research as "nascent" is hyperbole: Israel et al. (2018) refer to the yield spread within bonds' credit categories as "value." Houweling and van Zundert (2017) use a bond book-to-market factor in a robustness test.

We risk adjust BBM trading profits with two approaches. The first is cross-sectional Fama and MacBeth (1973, "FM") regressions. These control for bond return premia attributes, such as yield-to-maturity, credit rating, nearness to default, duration, credit spread, coupon, maturity, value outstanding, age, bond past returns (at several past-return horizons), and bid-ask spread, along with several attributes tied to equity returns—equity beta, equity market capitalization, equity book-to-market, accruals, earnings surprise, earnings yield, gross profitability, past equity returns, and industry. The second adjusts for risk with time series factor models. The latter include the Bai, Bali and Wen (2019, "BBW") factor model, both with and without augmentation by a term structure factor, and a customized 21-factor model subsuming the union of Houweling and van Zundert's (2017) and Bektić et al.'s (2019) factors. The BBM strategy's profits remain significant with factor risk adjustments. Moreover, like equity book-to-market, factor-adjusted profits are larger for "small bonds" (i.e., those with below median market capitalizations).

The risk-adjusted profits we document are not contaminated by market microstructure biases or by off-market pricing—offered to favored customers or from cost-efficient/oligopoly-exploiting central dealers. Our strategy's profits are also not due to the long-term return reversal effect of Bali et al. (2019). For the 20% of bonds that are closest to default or least liquid, the BBM signal has about the same efficacy as it does for the complementary bonds in the sample. The irrelevance of default risk and liquidity for BBM efficacy casts doubt on an omitted risk or liquidity factor explanation of the BBM anomaly. Likewise, the BBM anomaly is of similar economic magnitude when the sample is restricted to investment grade corporate bonds. However, BBM does *not* predict the returns of U.S. Treasuries, indicating that our controls adequately capture term structure effects. We also demonstrate that imputing monthly returns for U.S. Treasuries, computed from their intra-month prices at the transaction dates of our sample's more thinly traded corporate bonds, leads to the same "non-result." Finally, we show that the efficacy of the BBM signal for corporate bonds decays rapidly as the signal becomes stale. As noted earlier, the rapid decay in efficacy, particularly when compared to the slower evolution of the BBM attribute, is more suggestive of mispricing than risk mismeasurement or liquidity differences as the source of the BBM anomaly.

Robustness tests show that BBM is a better predictor of the risk-adjusted returns of a larger bond universe that includes all corporate bonds, including the junior, secured, and puttable bonds that academic studies typically avoid—compared to bonds that are senior, unsecured, and lacking exotic options. Tests also assess whether BBM merely proxies for other mispricing signals—specifically, a closely mirrored sibling of the equity mispricing signal developed by Bartram and Grinblatt (2018, "BG"). While correlated with BG, we find BBM's alpha effect is separate, significant, and stronger than the effect of the BG signal.

I. Data and Methodology

Prices for signals and bond returns largely come from the enhanced (pre-April 2020) and standard TRACE databases. TRACE's daily data are from January 2003 to August 2020 for trading signals, and from February 2003 to September 2020 for returns—with July to December 2002 used for the initial momentum control. Most of our analysis is limited to senior, unsecured, fixed-coupon bonds with no embedded options other than (typically, make-whole) call provisions (e.g., BBW, 2019; Chung et al., 2019). With our other filters, this bond-type covers an unbalanced panel of 8,925 different bonds (most existing for a limited portion of the sample period), 838 firms, and 458,139 bond-month observations.[5] One table studies all TRACE fixed-coupon bonds, covering 565,093 observations. Both TRACE samples exclude transactions reported to occur before the bond is issued or after it matures, as well as transactions reported as cancelled, attached to non-U.S. firms, denominated in non-U.S. currency, or issued by financial firms (SIC codes 60-69). The latter are structured around leverage and would overly influence results. We modify prices or other terms to their corrected values when TRACE indicates a retroactive correction. Mirroring BBW (2019), we also remove transactions with prices below 1/20 or above 10 times their face amount, bonds with remaining maturity of less than one year, and bonds in default at the time of trade initiation.

Our samples are about 30% larger than similarly filtered samples from WRDS Monthly Corporate Bond File, which records consecutive monthly returns as missing for bonds lacking transactions in the last five business days of the month. (Fewer than 25% of bonds trade on a month's last day.) Robustness tests also analyze returns from Merrill Lynch month-end trader marks, with the same start month as TRACE, but ending December 2016, covering 140,808 bond-month observations. For BG signal analysis, the issuing firm must have a single common equity share class of a U.S. corporation (share classes 10 and 11) in CRSP's Monthly Stock File, a share price of at least $5, a positive number of common shares outstanding listed on the NYSE, Amex, or Nasdaq, and positive total assets on the days of BG signal implementation.

We analyze month $t + 1$ profits from trading signals, primarily BBM, known by month t's end. Imputed prices from month $t + 1$ transactions help estimate full-month $t + 1$ returns. Unlike prior studies, we require a minimum eight-day gap between the transaction date of the bond price used for the signal and the first day of the return month. The latter is the earliest transaction date we might use to impute

[5] TRACE averages 1,149 bonds per month in cross-sectional regressions, since few bonds exist throughout the full sample period and the regressions require non-missing values for all regressors. The latter requirement is uniformly imposed across all specifications to facilitate comparisons. The paper's factor model regressions do not impose this constraint.

month $t + 1$'s return. As discussed later, this lengthy separation, an enhancement of measures used in equity studies to avoid bid-ask bounce, prevents microstructure biases from contaminating our findings. Note that the signal is known and assumed to be implemented at month t's end. It is merely the price inputs for the signal and estimated monthly return that require separate and distant transactions.

A. Return Construction

Unlike equities, bonds trade infrequently and often at large bid-ask spreads. To address these issues, we apply the martingale property. According to this property, an unbiased estimate of an asset's price on some date is its transaction price at some other date, adjusted for risk premia, the time value of money, and any payouts between the dates. These adjustments are small and closely captured by a bond's interest earned when transaction dates are close to the month-end price estimation date. For our sample, transactions used for price estimation are typically about 2–3 days from the prior or current month's end.

TRACE reports bond transactions' flat prices. Unless a bond is in default, a bond buyer pays the sum of the flat price and interest accrued, known as the "full" price. The full price change plus any coupon paid per dollar invested is an unbiased estimate of the bond's expected return. Thus, if earned interest per dollar invested (i.e., current yield)—the month's difference in accrued owed to sellers of the bond plus any paid coupon—completely captures the expected return, the flat price must follow a martingale. While monthly changes in accrued interest plus any distributions do not perfectly match the compensation for the time value of money and risk, they are close approximations, particularly for short time periods. Portfolio diversification makes the approximation more innocuous. Finally, any failing of the martingale hypothesis implies that our results are conservative, as explained in the paper's introduction. These insights validate substitution of flat bond prices from transactions at nearby dates for the month-end flat prices that would be observed for the same bond if the data were available. Specifically, a bond's month $t + 1$ return is its flat price change per dollar invested, as measured from month $t + 1$'s first and last transactions, plus the current yield from holding the bond over the entire month. Details are provided below.

End-of-Month Flat Bond Prices. The martingale property implies that the estimated end-of-month flat bond prices, P^E, are the mid-market end-of-month flat prices at which the bonds would trade, plus noise. The noise depends on the bond price's volatility between the date of the transaction used for estimation and the end of the month, as well as the spread charged by the transacting party who provides liquidity. For bond j's end-of-month $t + 1$ flat price, we use the flat price of the last month $t + 1$ trade in bond j. For example, to obtain the April 30, 2013 flat price, we might use the flat price of an April 26, 2013 trade. If there is no month $t + 1$ transaction for bond j, we treat the bond's month $t + 1$ return as missing.

Beginning-of-Month Flat Bond Prices. We estimate each bond's beginning-of-month flat price, P^B, as the flat price from its first trade that month. Thus, a bond's March 2013 beginning-of-month price comes from a March 2013 trade. If there is only one transaction in a month, the flat price of that transaction serves both as its beginning and ending flat price, tying its return only to the month's interest.

Monthly Returns. Using the end-of-month and beginning-of-month flat bond price estimates described above, we construct each bond's month $t + 1$ return as:

$$R_{t+1} = \frac{P_{t+1}^{E} + AI_{t+1} + C_{t+1}}{P_{t+1}^{B} + AI_{t}} - 1, \tag{1}$$

where P^B_{t+1} and P^E_{t+1} are the beginning- and end-of-month $t + 1$ imputed flat prices, AI_t is accrued interest owed at the end of month t, and C_{t+1} is the coupon (if any) awarded for holding the bond in month $t + 1$. We treat returns in two consecutive months as missing if their product is less than –0.04. A 20% monthly price increase followed by more than a 20% decrease, or the reverse, likely reflects error in recording the price used in consecutive returns. The cumulated six-month return, a momentum control, is computed analogously to equation (1), i.e., the return comes from a single beginning and a single ending price over the past return horizon. Analogous to equation (1), the six-month return used as a momentum control is adjusted for beginning and ending accrued interest, as well as coupons paid during the interval.

Due to Jensen's inequality, noise in equation (1)'s denominator, arising from beginning price imputation, upwardly biases its return estimates—analogous to the upward bias in equity returns shown in Blume and Stambaugh (1983). However, our results are based on the return spread between two quintile portfolios. If the return bias affects the long and short legs of portfolios in the same way, it is eliminated by looking at their return spread. Alternatively, if the bias is greater in the short leg (as implied by evidence on trading frequency), our return alpha spreads underestimate the true return and alpha spreads. This is distinct from the conservatism generated by martingale hypothesis violations. Recall that the latter conservatism is generated by discount (high BBM) bonds having flat prices that tend to appreciate, meaning partial month flat price changes understate full month flat price changes; likewise, premium (low BBM) bonds' imputed flat prices, which tend to depreciate, overstate full month flat price changes. The imperfections in our analysis thus imply wider BBM return spreads than reported.

Bonds in Default. TRACE reports the transaction prices of bonds in default. We use those prices when assessing trading signal profitability. Our data also pinpoint the day each default occurs. To facilitate risk adjustment, we exclude bonds in default at the time a trading signal is implemented (end of month t) but include bonds that commence default while our strategies are invested in them (month $t + 1$). The month t exclusion limits the fraction of defaulted bonds in our sample, yet avoids all bias from sample selection because the only default filter is from a feasible trading strategy choice.

Defaulted bonds trade "flat," obviating the need for equation (1)'s accrued interest adjustments to convert flat prices into prices paid. Moreover, the coupons promised by defaulted bonds are never paid in month $t + 1$. Unlike the flat prices of bonds that trade with accrued interest due, the flat prices of defaulted bonds cannot follow a martingale process—motivating adjustment of their beginning- and end-of-month $t + 1$ price estimates. The adjustment we apply deliberately underestimates defaulted bonds' returns.[6] This makes our return spread estimates conservative because we understate the return of long positions in defaulted bonds and there are no defaulted bonds in our strategies' short positions. The conservative approach is "overkill," as transactions in bonds that commence default in month $t + 1$ are remarkably rare, even for the strategies' long positions—constituting only 0.02% of their transactions.

Original Issue Discount Bonds. A similarly rare situation exists with bonds issued at deep discounts. Fewer than 0.1% of bonds have offering prices below \$50, and 99.8% have offering prices above \$90. Moreover, the average issue prices of the five BBM quintile portfolios are all close to \$99.5. The flat prices of such original issue discount bonds appreciate rather than (approximately) follow a martingale. However, sizable discounts are rare, the numbers of days of amortization are generally small, and the distribution of such bonds across BBM quintiles is relatively symmetric. For these reasons, adjusting the martingale price estimate for original issue discount bonds would increase the returns of BBM quintile portfolios by only negligible amounts. Eschewing the adjustment, as we do, has no detectable effect on the return difference between any pair of quintile portfolios and helps offset the Jensen's inequality bias discussed earlier.

B. Signal Construction

Price measurement error shared by the month-end signal and subsequent return generates correlation between the two. Constructing end-of-month t signals from transaction prices at least eight calendar days before the first day of month $t + 1$ avoids this pitfall. The multi-day gap addresses trade splitting and workouts. Consider a 120 million U.S. dollar customer bond sale to one or more dealers, executed as three 40 million U.S. dollar sales on three consecutive days: April 29, 30, and May 1. Such trades yield three daily price estimates at bid prices, assuming the bond lacks other trades. Bid prices artificially inflate any BBM signal employing them, as well as May's return if April 30's (e.g., WRDS computation of the bond's return) or May 1's transaction provides the return's beginning price. Trade splitting at the ask or favorable pricing by dealers to trades straddling a month's end induce similar correlation. Scenarios that artificially induce

[6] Specifically, if the imputed beginning-of-month price is quoted flat due to default, equation (1) substitutes the flat price of the first transaction preceding the transaction used for the signal (hence, pre-default) as P^B, uses the end-of-month (hence, post-default) price for P^E, and omits accrued interest and coupons in the numerator, but not the denotator.

correlation between BBM signals and subsequent returns become less likely the larger the gap between the prices used for signals and returns. Our eight-day gap ensures that correlations between estimated BBM and estimated returns stem from signals that truly predict returns rather than any microstructure bias.

Bond Book-to-Market Signal. Book value per \$100 face amount is a bond's amortized issue price. Table 1 Panel A reports the distribution of issue prices, sourced from the Mergent Fixed Income Securities Database (FISD). For most bonds, the FISD issue price is near \$100.[7] If the bond is issued at a discount or premium, we apply the accounting rule that linearly amortizes the premium or discount to maturity on month-end dates to arrive at the bond's (end-of) month t book value. For the approximately 30% of cases where FISD lacks the issue price, we omit the bond as a candidate for a potential trade.

Our month t BBM signal is Book/P^S. The signal's flat price per \$100 of face amount, P^S, is taken from the bond's most recent transaction (excluding month t's last seven days). The approach may employ some prices from stale trades, but since the information represents what is available at the end of month t, it can direct trades at that instant in time. It is also conservative, since signals based on stale prices are likely to be less effective. Table 1 Panel B reports the distribution of time between the dates of the transaction used for P^S in the BBM signal and the transaction used for beginning price P^B in the bond's month $t + 1$ return estimate. For the senior unsecured bonds that researchers traditionally study ("traditional bonds") and that we focus on in all but Table 9, the median gap between the signal date and that latter price is 11 days; the average is 16 days (Panel B's first row). About 10% of the gaps exceed 25 days.

Figure 1's timeline shows consecutive transactions in a bond as dots. It depicts the prices used for signal and return construction. P^S is the transaction price used for month t's signal. P^B and P^E are intra-month flat transaction prices used as beginning and ending flat prices for month $t + 1$'s return. The pair serves as the imputed flat prices at their nearest hashmarks, which separate months. Figure 1 shows P^S as originating in month t, but it could come from a prior month if the bond lacks a month t transaction.

Bartram and Grinblatt Mispricing Signal. We later study whether a bond-centric implementation of BG's mispricing measure generates a signal that predicts a bond's future return and subsumes the BBM signal. Each bond is assigned a firm-level BG mispricing measure. The BG signal first computes an estimated month t market value of each firm's total liabilities—including bonds and other debt obligations (e.g., commercial paper, accounts payable, bank loans) that lack TRACE-reported transactions. Our estimate of the month t market value of firm i's total liabilities, $V_{i,t}$, is the sum of the market capitalization of

[7] With \$100 assumed as the book value of all bonds, BBM's ability to predict returns is highly significant, but slightly reduced.

its bonds, computed from their most recent TRACE transaction prices (excluding transactions less than eight days before the first day of month $t + 1$), plus the aggregate book value of firm i's other liabilities.

The BG bond mispricing signal measures deviations of a firm's aggregate debt obligations from monthly predictions based on its accounting variables. Each month t, we regress each firm's $V_{i,t}$ on its 28 most commonly reported items from Compustat's point-in-time database. The regression predictions represent month t peer-implied norms for each firm's total liabilities. Each bond is assigned the BG signal of its issuing firm, which is the percentage deviation of the firm's predicted $V_{i,t}$ from its actual value.

C. Alpha Tests for Signal Efficacy and Control Variables

The BBM and BG signals sort bonds into quintiles at month t's end. Quintile 5 has the most value-oriented (BBM signal) or underpriced (BG signal) bonds. We primarily analyze month $t + 1$'s bond returns within these quintile portfolios, employing FM cross-sectional regressions as well as structural and factor models.

FM Regression Coefficients on BBM (or BG). Here, the monthly regression's unit of analysis is the bond. We cross-sectionally regress month $t + 1$'s bond returns (computed using Section I.A's procedures) on BBM (or BG) expressed as quintile dummies or normal scores and quintile dummies for numerous control variables. The coefficients on each regressor are then averaged across months. The controls consist of bond characteristics and issuing firms' equity characteristics measured (in contrast to the signal's 8-day gap) as close to the end of month t as possible. These controls are rooted in past literature and textbooks.[8] They include each bond's coupon rate, yield-to-maturity, credit spread, credit rating, value outstanding, time to maturity, duration, age, past 7-month return excluding the prior month ("bond momentum"), past 1-month return ("bond reversal"), bid-ask spread, and nearness to default. Equity characteristics include equity market beta, equity market capitalization, equity book-to-market, past 1-month stock return ("short-term reversal"), past 5-year stock return excluding the prior year ("long-term reversal"), past 12-month stock return excluding the prior month ("momentum"), accruals, earnings surprise ("SUE"), gross profitability, and earnings yield. Many controls are highly correlated, complicating inferences from their coefficients. Most FM regressions also include market microstructure/liquidity controls that are measured in the return month $t + 1$, as well as industry dummies. Robustness tests explore parametric controls.

We employ four main specifications of nonparametric regression controls. The first has industry controls; the second adds market microstructure controls; the third adds controls for bond characteristics;

[8] In addition to several papers cited earlier, Grinblatt and Titman (2002, Chs. 2, 23) discuss YTM, maturity, duration, and credit rating, Nozawa (2017) studies credit spread, Blume and Stambaugh (1983) study bid-ask spread, Jostova et al. (2013) focus on past returns, Warga (1992) relates bond age to returns, and Schaefer and Strebulaev (2008) analyze nearness to default. BG's (2018, 2021) equity controls are the same as ours. Other research on equity controls is cited in the introduction's discussion of equity market efficiency.

the fourth adds equity characteristics of the bond issuer. The many controls in category-oriented FM regressions represent a high dimensional matrix classification of each bond, akin to matrix pricing commonly used by Wall Street to mark YTMs and prices of thinly traded bonds. Here, they represent attributes that likely predict bond returns. Internet Appendix A describes these characteristics in more detail, along with the 28 items used for the BG signal.[9] A robustness check with a necessarily shortened sample period and smaller cross-section includes the bond's past 3-year return, skipping a year ("bond long-term reversal").

Flat price imputation, used for Equation (1)'s dependent variable generates no bias in the FM slope coefficients. Because the dependent variable R_j is bond j's true (but unobservable) full month return r_j less noise, e_j, regressing the imputed return R_j on an observable attribute X_j

$$r_j - e_j = c_0 + c_1 X_j + u_j$$

has a plim for c_1 equal to the slope coefficient that the unobserved true return would have, since

$$\text{cov}(r_j - e_j, X_j)/\text{var}(X_j) = \text{cov}(r_j, X_j)/\text{var}(X_j).$$

This stylized example illustrates that the c_1 estimate from intra-month flat prices is a consistent estimate of the unobservable true full month return's c_1. If X_j is a categorical dummy, c_1 is the return difference of two equal-weighted portfolios. Its noise component is diversified away in FM time series averaging.

Structural Models. FM regressions can also be combined with structural models. Structural models view corporate bonds and equity as contingent claims on the firm's assets. One typically uses structural models to calculate bond prices, yields, or credit spreads, but they also have implications for returns.[10] Here, structural models imply that, over very short time periods, corporate bond returns should be close to perfectly correlated with a portfolio of riskless bonds and same-firm equity. Hedging out the equity component on the left-hand side of the FM regression adjusts for most of the risk premium linked to credit risk. To identify hedge ratios, we run a panel regression of bond returns on their own-equity returns interacted with the control dummies used for the FM regression. This generates equity hedge ratios for each bond-month observation from the panel's coefficients and monthly bond attributes.

Factor Model Intercepts. Regressing the time series of excess returns (above 1-month LIBOR) of five BBM quintile portfolios on factor portfolio returns is an alternative to FM regressions for risk adjustment.

[9] The 28 BG signal items, outlined in Internet Appendix A, are the same regressors used for the BG (2018) signal. Point-in-time data ensure that debt fair value estimates were available to investors when the BG signal motivated a trade.

[10] Structural models are poor at explaining bond prices or spreads of wide categories of bonds. Eom et al. (2004) try to fit the credit spreads of 182 bonds to structural models, finding they do not match observed credit spreads (a control we use). Huang and Huang (2012) conclude that these models are deficient at pricing bonds, even at the ratings level. Huang et al. (2020) document that the models fail to fit CDS data. Collin-Dufresne et al. (2001)'s bond-level regressions of credit spreads on stock returns and other control variables show that structural models do not work well either.

The regression intercepts or spreads between the intercepts represent alpha and should be zero in an informationally efficient bond market. We begin with BBW's (2019) five factors: the bond market, credit, downside risk, liquidity, and reversal factors. Factor construction in our paper, using bond data from TRACE, follows BBW's (2019) procedures.[11] Data from Merrill Lynch is required for downside risk in the sample's first three years, when the factor requires data that precedes TRACE's initiation.

In addition, we use an augmented BBW 6-factor model that adds a term structure factor to BBW's five factors, and a customized 21-factor model consisting of 13 equity and 8 bond factors. The 13 equity factors are Fama and French's (2015) five factors, short-term reversal, momentum, and long-term reversal, all from Kenneth French's data library, as well as the equal-weighted excess returns of each bond issuer's equity within each of the five BBM quintiles. The eight bond market factors consist of two bond factors for the default and term spreads used in Chordia et al. (2017), bond momentum and bond value as computed for government bonds in Asness et al. (2013), and four excess return factors (above the risk-free rate) tied to U.S. bond indices from DataStream: the Intermediate Treasury, Long-Term Treasury, Corporate Investment Grade, and Corporate High-Yield Indexes.

D. Summary Statistics for the Overall Sample

Table 2 Panel A reports summary statistics for BBM and other attributes of the senior unsecured bonds and their issuing firms. Each row reports the time series average of the cross-sectional means of each variable using all of these traditional bonds (Column 1) and all traditional bonds within each BBM quintile (Columns 3–7). Q1 represents the 20 percent of bonds each month with the smallest BBM, averaging a BBM of 0.85; Q5 represents the highest BBM quintile, averaging a BBM of 1.09. Column 2 also reports the time series average of the cross-sectional correlations of the characteristic with BBM.

BBM correlates with the BG bond mispricing signal, with an average correlation of 0.29, and BG monotonically increases across BBM quintiles. BBM correlates with other variables as well. High BBM bonds tend to have poorer credit ratings (AAA=1, …, D=22, with 10 or less indicating investment grade) and are closer to default.[12] They also have higher YTMs, lower market value, higher bid-ask spreads,

[11] We first calculate each bond's daily price as its volume-weighted average daily price, for all bonds in TRACE and Mergent FISD meeting BBW's (2019) filters. When TRACE shows trades in the last five business days of months t and $t+1$, we compute the bond's return from consecutive month-end daily prices (adjusting for accrued interest and coupons paid). If month t lacks a qualifying month-end daily price, we compute month $t+1$'s return using the earliest daily price in the first five business days of month $t+1$. If neither approach is possible due to lack of qualifying prices, we treat month $t+1$'s return as missing. Factors face-value weight these returns for specific subsets of bonds, as in BBW.

[12] Default risk is quite low. Even the highest BBM quintile averages an investment grade (IG) rating. IG bond types show a similar-sized BBM anomaly. We also control for nearness to default (the negative of the distance to default in Schaefer and Strebulaev, 2008), computed as the z-value corresponding to the default probability from an adaptation of the Black-Scholes model. Nearness to and distance from default thus generate identical default probability quintiles. The firm is in default when nearness to default is positive infinity; default probability is below one-half with negative nearness to default.

greater trading volume, larger numbers of trades, and been issued more recently and by firms with more bonds. Lastly, they come from firms with higher equity beta, poorer returns over the past year, larger equity book-to-market, and lower earnings/stock price ratios. By contrast, the lowest quintile of BBM bonds have the highest returns over the past six months (bond momentum). These bonds also come from firms with the highest stock returns over the past year (equity momentum) and are issued by larger firms.[13] Bond maturity and duration, while concentrated in the two extreme BBM quintiles, are greatest within the 20% lowest BBM bonds. Combined with the fact that lower credit risk tends to extend the effective maturity of actual bond payments, and holding coupon rate the same (which has opposing duration and tax effects on expected returns), it is apparent that the greatest risk from shifts in the risk-free term structure lie within the 20% lowest BBM bonds, which the BBM strategy sells.

The introduction's martingale discussion noted that the flat prices of BBM Q5 bonds, which trade at a discount, tend to appreciate, while Q1 bonds tend to depreciate—particularly with enough time and when BBM is driven by past yield curve changes. Thus, Q5 bond purchasers tend to earn capital gains, while Q1 purchasers earn capital losses, even if both bond types earn the same return. (The other return component, current yield, tends to offset expected shrinkage of flat price discounts and premiums.) When realized, the gains and losses will generally be taxed at lower rates and in the more distant future than accrued interest or amortization. Thus, tax considerations argue for negative Q5 – Q1 risk-adjusted return spreads. Similar tax arguments apply to BBM assignments from changes in the market price of credit risk or a bond's default probability. We now analyze raw return spreads before turning to risk adjustment.

Table 2 Panel B reports the average month $t + 1$ returns of five BBM-sorted portfolios in the columns labelled Q1 – Q5. The panel's first two rows correspond to equal- (EW) and value- (VW) weighted quintile portfolio returns, respectively, both of which exhibit nearly monotonic increases across BBM quintiles. For example, the lowest BBM EW quintile portfolio earns 57 bp per month, while the highest earns 101 bp per month. Panel B also shows the average monthly return for the full sample (66 bp EW and 57 bp VW, a more than 1% annualized difference), the average monthly cross-sectional correlation between returns and BBM (0.04), the average monthly spread between the returns of the largest and smallest BBM quintiles (44 bp EW and 41 bp VW, both significant), as well as the fraction of months with a positive Q5 – Q1 return spread (63% EW and 59% VW, both significant). The t-statistics of the spread correspond to annualized Sharpe ratios of 0.92 (EW) and 0.85 (VW), respectively. Both Sharpe ratios exceed the 0.40 Sharpe ratio for equity HML (over a longer sample period) reported by Ehsani and Linnainmaa (2022). The last two rows of Table 2 Panel B show the breakdown of the top rows (EW) by bond

[13] Nozawa (2017) and Chordia et al. (2017) show corporate bond issuers are mostly large firms (above NYSE median size).

size. Small bonds have larger returns within each quintile and a larger BBM effect than large bonds.[14] The small bond BBM effect comes from Q5, for which the small minus large bond return is 27 bp per month—nearly twice the small minus large spread for Q1 and the largest size spread for any quintile.

Table 2 Panel B's return spreads are not temporary price changes that subsequently reverse. Percentage changes in flat prices from the return's ending price to the next price (from month t + 2's first trade or latter) are –0.001 for the EW Q5 portfolio and –0.090 for EW Q1 (table-omitted for brevity.) Thus, returns formed from the prices of month t + 1 and t + 2's initial transactions, rather than from month t + 1's first and last trades, would marginally increase BBM's reported extreme-quintile spread.

Panel B omits bonds lacking a month t + 1 trade and assigns zero flat price change to bonds trading just once in month t + 1. Such choices might inflate Panel B's spreads, albeit negligibly, if no-trade bonds have small unobserved spreads or one-trade bonds' spreads are negative over full month t + 1. But the opposite is true. Table 2 Panel C reports each quintile's monthly return, measured from the trade just prior to the signal price's trade date to the first trade after month t + 1. The returns shrink inter-month flat price changes by the number of months, (a fraction exceeding one), between the beginning and ending transactions generating each price pair, while each return's current yield component is over the full month t + 1. Panel C shows a *larger* return spread for no-trade bonds than the full sample's spread and a *positive* flat price change for one-trade bonds—the latter reflected by the difference in Panel C's two bottom rows.

Table 2 Panel D reports each BBM quintile's joint distribution of beginning and end bid-ask pairs for month t + 1's TRACE-sourced returns. It reports the fraction of returns that come from the nine pairings of bids (customer sale to a dealer), asks (customer buy from a dealer), and mids (dealer-to-dealer transaction) attached to beginning and ending prices. A bid beginning price tends to have a higher return, while a bid ending price tends to have a lower return, with the reverse for asks. Applying the bid-ask spread from each quintile (Panel A) to the joint distribution in Panel D implies that both Q1's and Q5's returns are upwardly biased, by 1 bp and 3 bp, respectively. Their difference, 2 bp, is negligible. Hence, Table 2 Panel B's returns are not driven by return computations that sometimes rely on bid and ask prices.

II. Bond Book-to-Market and the Cross-Section of Expected Bond Returns

Table 2 Panel B's 5% annualized BBM-based return spread is large given bonds' low volatility. However, many return-influencing (and often risk-related) attributes correlate with BBM. We therefore analyze BBM's marginal effect, controlling for these attributes. Both cross-sectional FM regressions and time series factor model regressions show that BBM does not proxy for return-predicting attributes or factor betas.

[14]The two sequentially sorted rows do not average to the top row because some bonds lack face amount outstanding data.

A. Fama-MacBeth Cross-Sectional Regressions

The FM approach regresses the cross-section of next month's bond returns (in percentage points) on their BBM signal and other bond and equity characteristics known at the time of trade initiation:

$$R_{j,t+1} = a_t + \gamma_t BBM_{j,t} + \sum_{s=1}^{S} c_{s,t} X_{j,s,t} + e_{j,t+1}\,. \tag{2}$$

In equation (2), $BBM_{j,t}$ is the month t BBM signal for bond j, and $X_{j,s,t}$ is the end-of-month t value of characteristic s of bond j (or its issuer) including industry fixed effects. The FM procedure averages the monthly coefficients over time and tests whether the average significantly differs from zero.

FM Specification. To assess the economic magnitudes of BBM's return-predicting coefficients, Table 3 Panel A's four odd-numbered specifications transform all regressors into quintile dummies Q1, …, Q5 and regress bond returns on dummy variables corresponding to Q2 through Q5, with Q1 omitted due to the regression intercept. For brevity, Table 3 Panel A only reports the coefficients for the Q5 dummy variables, which represent the return spread from Q5 – Q1 holding other regressors fixed. Specifications 2, 4, 6, and 8, which study a parametric version of the signal, replace the BBM quintile dummies with the BBM normal score, which is the BBM ratio transformed into a standardized normally distributed regressor.

Specifications 1 and 2 regress bond returns on BBM and industry dummies. Specifications 3 and 4 add market microstructure/liquidity controls to Specifications 1 and 2 that roughly proxy for the precision with which the martingale approach estimates month $t + 1$ returns. They include the number of bonds from the issuing firm in month $t + 1$, the percentage of the market value of the issuing firm's bonds with month t signals that trade in month $t + 1$, and a pair of controls for the (absolute value of the) number of calendar days between the first (last) day of the month and the transaction date used for beginning-of-(end-of-) month $t + 1$ prices. Specifications 5 and 6 add bond attribute controls to Specifications 3 and 4. Finally, "kitchen sink" Specifications 7 and 8 add equity and firm characteristics to Specifications 5 and 6. The bond and equity attributes are described in the paper's methodology section.

All specifications tell a similar story about BBM's role in the cross-section of bond returns. Specification 1 shows that BBM Q5 bonds outperform Q1 bonds by an average of 44 bp per month (t = 3.62), controlling for industry fixed effects. The coefficient of 0.14 on the parametric BBM signal is also significant (t = 3.13) as Specification 2 shows. Specifications 3 and 4 illustrate that market microstructure controls have little effect on the results: BBM's average coefficient is virtually the same, whether comparing Specification 3 with 1, or 4 with 2. Omitted for brevity, the relatively small effect of the market microstructure regressors applies to the remaining two specifications as well. This suggests that our martingale procedure for identifying month $t + 1$ returns is unlikely to have distorted inferences. The addition of bond-specific controls (Specifications 5 and 6) reduces BBM's influence on a bond's month $t + 1$ return by about two fifths, but the BBM effect remains highly significant. Specification 7 and 8's addition of controls related to equity returns increases the BBM Q5 coefficients by about one fifth compared to Specifications 5 and 6, and also increases their significance. Specifications 7 and 8 also establish that equity book-to-market does not predict bond returns once BBM is controlled for. Results are also not driven by outliers. Eliminating the observations that rely on the top 100 or bottom 100 bond prices has a negligible effect on our findings.

So, how strong are these results? Specification 7's 4.05 *t*-statistic corresponds to an annualized Sharpe ratio of 0.96, which exceeds both the S&P 500's and the Fama and French (1993) HML factor's Sharpe ratio. Compared to equity returns, bond returns have far lower volatility and predominantly come from transactions associated with larger firms, making the size of the BBM alpha spread relatively more impressive. Moreover, compared to its equity cousin, the BBM effect has far superior risk controls. In addition to quintile dummies for yield-to-maturity, default risk, bond age, and liquidity, equation (2)'s cross-sectional regressions control for the effect of maturity and industry, among others.

Callable Bonds. Robustness tests dismiss concerns that BBM Q5 outperforms Q1 because of inadequate controls. For example, bonds tend to be called by their issuing firms when their fair value (in the absence of a call) exceeds the call price. However, filtering out bond returns in months approaching call dates or adding controls for bond call dates suggests callability has little effect on the BBM alpha spread.

Robustness. Table 3 Panel B, which parrots Panel A Specification 7's use of all FM controls, offers further proof of the robustness. First, quintile dummy control variables, used in Table 3 Panel A to better proxy for a nonlinear relationship, do not explain our findings. Panel B's Column 1 shows similar results with parametric control variables, yielding a BBM quintile spread of 29 bp (t = 4.52). The martingale assumption is also innocuous. End-of-month trader marks in the Merrill Lynch database instead of bond returns from transactions offer alternative returns for a smaller set of more liquid bonds. With the Merrill data, BBM's (unreported) Q5 – Q1 raw return spread is 44 bp (t = 2.65) for equally weighted portfolios and 44 bp (t = 2.85) for value-weighted portfolios. The associated alpha spread (Panel B Column 2) is 20 bp per month (t = 2.52). Using the Merrill marks for the prices of the BBM signal as well (Column 3) generates a larger and far more significant alpha spread of 50 bp per month (t = 5.03), but this finding has potential bias from error in the price mark shared by both the BBM signal and the return's beginning price.

Structural Models. Table 3 Panel B also rebuts arguments that Table 3 Panel A's significant alpha spreads stem from failure to properly control for the structural model implication that distressed bonds resemble equity. Earlier, we noted that BBM Q5 bonds are not distressed because they exhibit negligible default rates, while Q1 bonds experienced no defaults. We also noted the extensive controls for credit spreads, bond rating, and default in Table 3's FM regressions. Punctuating our claim is Column 4 in Table 3 Panel B, which reruns Panel A's Specification 7 (all controls) with equity-hedged bond returns as the dependent variable. Bond j's month $t+1$ hedged return subtracts the product of its end-of-month t hedge ratio (described earlier) and the issuing firm's month $t+1$ equity return in excess of LIBOR from the bond's month $t+1$ return. The hedge eliminates the bond's asset risk premium component. Column 4's results here resemble Table 3 Panel A. BBM Q5's same-firm equity-hedged bond returns outperform Q1's by 32 bp per month ($t = 4.82$). The similar equity-hedged and unhedged BBM quintile coefficients indicate that structural models are unlikely to play a successful role as supplements or replacements for Table 3's categorical regressors. Finally, if BBM Q5 merely proxied for poor default controls, BBM should predict the firm's equity return. However, Table 3 Panel B (Column 5) shows that when the firm's equity return is the dependent variable, the BBM Q5 coefficient is –0.082 and insignificant ($t = –0.71$). In sum, BBM predicts bond returns and equity-hedged bond returns, but not same-firm equity returns. Later study of interaction effects supports this finding. Moreover, the equity premium associated with default reflects outcomes where equity is nearly wiped out. In unreported results, using a dummy for whether the equity return is below –75% as the dependent variable yields a BBM Q5 coefficient of 0.079 ($t = 1.50$).

Investment Grade Bonds. Is BBM Q5's outperformance of Q1 due solely to below investment-grade bonds? Table 3 Panel's rightmost column investigates this issue by studying the subsample of traditional bonds that are exclusively investment grade (IG). After sorting IG bonds into BBM quintiles, the rightmost column reports Specification 7 of Table 3 Panel A's FM regression. The BBM Q5 coefficient for the IG subsample of 0.307 ($t = 5.97$) is similar to the coefficient in Table 3 Panel A, but more significant. With an independent sort of IG and BBM, the (unreported) comparable BBM Q5 coefficient is 0.321 ($t = 5.01$).

Long-Term Return Reversals. Daniel and Titman (2006) and Gerakos and Linnainmaa (2017) link book-to-market's equity return predictability to the ratio's correlation with long-term past returns and, accordingly, changes in firm size. Bali et al. (2019) show that a bond's 3-year past return, measured from month $t-48$ to $t-13$, predicts return reversal. We omitted a 3-year past return control because it limits sample size: Requiring 48 months from the sample's beginning date halves the average number of bonds in the cross-section and cuts 42 months from the sample period. Nevertheless, in horse races between 3-year past return and BBM, using Table 3 Panel A's key specifications (plus the 3-year past return), the 3-year past return's coefficient is never significant and always economically small. For example, in specifications analogous to Table 3 Panel A's Specifications 5 and 7, the BBM Q5 coefficients are 0.250 ($t = 2.55$) and 0.303 ($t = 3.29$), while the 3-year past return Q5 coefficients are 0.006 ($t = 0.08$) and –0.016 ($t = –0.20$), respectively. These results, based on a shorter sample period with fewer bonds than Table 3 Panel A, suggests that BBM subsumes the 3-year past return effect as a predictor of corporate bond returns.

B. Factor Model Time Series Regressions

As an alternative to FM regressions, Table 4 reports factor model alphas and factor betas of EW and VW quintile portfolios sorted on the BBM signal using several factor models. Compared to Table 3 Panel A's FM cross-sectional analysis, Table 4's time series factor model regressions include bond observations that lack data on the control characteristics. They also facilitate alpha analysis of each of the BBM quintile portfolios and the use of both equal and value weighting.

For BBM quintile portfolio q, Table 4 Panels A and B run time series regressions of the quintile portfolio's returns (in excess of 1-month U.S. Dollar LIBOR) on five or six risk factors,

$$r_{q,t+1} = a_q + \sum_{l=1}^{6} \beta_{q,l,t+1} F_{l,t+1} + \varepsilon_{q,t+1}. \tag{3}$$

The intercept a_q is the risk-adjusted return or "alpha" of the quintile portfolio. All factor model regressions report test statistics derived from Newey and West (1987) standard errors. If systematic risk factors explain differences in bond returns for portfolios stratified by BBM, the risk-adjusted returns a_q of the BBM quintile portfolio should be indistinguishable from zero. Table 4 Panels A and B report the alphas and factor betas, as well as the spread in the Q5 – Q1 risk-adjusted returns.

BBW Factors. The BBW 5-factor model controls for overall bond market risk, credit risk, downside risk, liquidity risk, and short-term bond return reversal factors; the augmented BBW 6-factor model adds a term structure factor. The first row of each of Panel A's top half (EW portfolios) and bottom half (VW portfolios) shows each quintile's BBW risk-adjusted returns. Table 4 Panel A's EW 19 bp alpha spread is smaller than the alpha spread (BBM Q5 coefficient) from any of Table 3 Panel A's odd-numbered (non-parametric) specifications, including the two lowest: Specifications 5 and 7 report alpha spreads of 27 and 32 bp per month, respectively. The VW spread, 12 bp per month, is smaller than the EW spread and statistically insignificant. Part of the reason for the small EW and VW alpha spreads in Table 4 Panel A is the BBW model's 5-factor selection. It controls for some sources of factor risk, like credit risk, which reduce the Q5 – Q1 spread. However, it lacks a factor control for the term structure of interest rates, even though bonds with similar maturity tend to covary more with each other than with different maturity bonds. The BBW 5-factor model also lacks factors for many of the other controls in Table 3 Panel A's FM regression, like bond size or yield. This may partly explain why the alphas from Tables 3 and 4 differ.

To control for factor risk arising from the term structure, Table 4 Panel B supplements the BBW factors with one additional factor. Because both coupon and credit rating influence the effective maturity of a bond, we create a term structure factor in the spirit of BBW. To this end, we conduct independent triple sorts of bonds into 125 face-value-weighted portfolios based on maturity, coupon and credit rating.

We then take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, then do the same for the bottom 20% for the short position. The difference in returns between these two extreme maturity quintiles is our term structure factor. Table 4 Panel B's augmented BBW factor model shows that adding this term structure factor increases the EW alpha spread to 23 bp and the VW spread to 18 bp, both statistically significant. The latter spreads are closer to the pair of comparison spreads obtained from Table 3 Panel A's FM regressions.

Biases due to Jensen's inequality and the distribution of bid and ask prices in returns prevent assessment of whether Table 4's observed spreads are driven more by the long or the short end. However, if the bias was the same across all quintile portfolios and the true alphas of the five EW quintile portfolios averaged to zero, the respective EW alphas in Panels A and B would be 22 bp and 19 bp lower than reported. Reducing each alpha in Panel A by the 22 bp would generate Q1 and Q5 intercepts of –0.02 and 0.18, respectively. Panel B's alpha reduction of 19 bp implies Q1 and Q5 intercepts of –0.06 and 0.17, respectively. Based on these transformations, alpha spreads largely come from the long end (Q5).

Bond Size. Table 4 Panel C's top four rows illustrate the effect of bond size on the factor model's EW alpha with the BBW 5-factor and augmented 6-factor models.[15] With both models, bonds with less than intra-quintile median market capitalization have larger and more significant alpha spreads than bonds with larger value outstanding. With the 5-factor model, EW portfolios of "large bonds" exhibit no significant alpha spread. With the augmented 6-factor model (3rd and 4th rows), the small bond alpha spread is a significant 28 bp, which lies between the 27 and 32 bp alpha spreads from Specifications 5 and 7 in Table 3 Panel A's FM regression. However, the 20 bp large bond spread, while significant, is far smaller. If mispricing accounts for BBM alpha spreads, this finding, along with the VW finding for the BBW 5-factor model, suggests that large bonds may be more efficiently priced than small bonds. The far greater efficacy of BBM as a predictor of risk-adjusted returns for small bonds mirrors a parallel finding for equities.

Alternative Factor Models. An alternative to the BBW factor model regressions above supports the conclusion that there is a significant BBM alpha spread after controlling for factor risk. A customized 21-factor model, described in Section I.C, generates a significant 18 bp alpha spread for EW portfolios (t = 2.38). This alpha spread, seen in Panel C's fifth row, is the difference between the BBM Q5 intercept (38 bp), which is statistically significant (t = 5.30), and the BBM Q1 intercept (20 bp). The factor model's VW alpha spread of 14 bp (t = 2.12) is omitted from the table for brevity.

[15] The small and large rows do not average to Table 4 Panel A's EW alphas because some bonds lack data on their size.

III. Understanding the BBM Alpha Spread: Risk or Mispricing?

We now present additional evidence on the two competing explanations for BBM's return predictive success: first, that BBM proxies for omitted risk or liquidity controls; second, that extreme BBM quintiles contain mispriced bonds. This evidence includes BBM's decline in signal efficacy with delayed implementation, its similar efficacy across bond groups sorted on default risk or liquidity, BBM's inability to predict U.S. Treasury returns, and the insufficient risk adjustment attached to covariance with a BBM-linked factor.

A. Signal Delay

Figure 2 plots alpha spreads (i.e., BBM Q5 dummy coefficients from Specification 7 of Table 3 Panel A) for signal delays ranging from zero to eleven months. In contrast to Table 3 Panel A, Figure 2's returns always commence January 2004 irrespective of signal lag, ensuring apples-to-apples comparisons across differing lags. Its 30 bp per month alpha spread with no delay, i.e., first signal from December 2003, nearly matches the 32 bp coefficient reported in Table 3 Panel A despite the shorter return series. Figure 2 indicates an alpha spread decline to 9 bp when the signal delay is two months, losing about 70% of its efficacy. The spread meanders with further delay, ranging from 2 bp to 12 bp with a slow downward trend.

Figure 2's rapid decay rules out omitted risk or liquidity controls as the source of the BBM anomaly. Bonds with extreme BBM ratios may ultimately exhibit less extreme BBM. However, BBM is an attribute that evolves slowly, and generally, large price changes are required to move a bond out of an extreme BBM quintile. Most extreme quintile bonds remain in their quintiles for several months and, for some, even years.[16] The BBM attribute's slow evolution implies that if BBM *broadly* proxies for omitted risk or liquidity attributes, stale BBM signals should predict bond returns. But this is inconsistent with Figure 2's decay!

Calibration of delay's effect on quintile membership supports our view that BBM cannot be a broad proxy for risk or liquidity. More than 85% of the extreme quintiles' bonds persist in those quintiles in the next month, yet signal efficacy diminishes by 42%. With the two-month lag, alpha declines by 70%, but more than 80% of this stale strategy is dedicated to bonds that remained in quintiles 1 and 5. Moreover, as time evolves, bonds leaving the extreme quintiles generally move to adjacent quintiles. The alphas of

[16] BBM changes slowly with wide cross-sectional variation, just as Gerakos and Linnainmaa (2017) document for equity book-to-market. To prove that these features make BBM's quintiles stable, we computed survival rates: the percentage of each BBM quintile's month *t* investment remaining in the quintile's month *t* bonds at the end of months $t + 1$, $t + 2$, and $t + 3$. With one-monthly delay, the time series averages of the percentages of "old bond" investment are 89%, 73%, 67%, 67%, and 82% for Q1, Q2, Q3, Q4, and Q5, respectively. Thus, the one-month survival rates for bonds in the two extreme BBM quintiles exceed those of the three interiors quintiles. For Q1 and Q5, the 2-month survival rates are 85% and 76%, respectively: only an additional 4% and 6% of bonds leave Q1 and Q5 in the subsequent month, respectively.

adjacent quintiles have tighter spreads with their more extreme neighbors than the two extreme BM quintiles have with each other. Indeed, the unreported coefficients on BBM quintiles 2–5 are monotonically increasing and significant in all of Table 3 Panel A's odd-numbered specifications.

The pattern of alpha decay combined with the size of BBM's extreme-quintile spreads also rule out BBM as a *narrow* proxy for the omitted risk or liquidity attributes of a small proportion of these quintiles' bonds. As a narrow proxy, the omitted risk or liquidity attributes must earn enormous and implausible premia to account for the extreme-quintiles' observed alpha spread, then disappear once the bonds carrying those premia exit their BBM quintile. With alpha spreads about twice the spread in YTM, the hidden risk or liquidity attributes would have to earn at least 20 times the Q5 – Q1 spread in *promised* yields if BBM proxied for the omitted controls of 20% of the BBM Q5 bonds. An omitted risk or liquidity attribute earns just one-sixth of the needed spread if it earns a five percent per year spread for this narrow set of bonds. Five percent is what the typical traditional bond earned over Treasury bills during our sample period without controls, while the narrow proxy hypothesis says BBM captures many times this premium *as a spread* missed by our controls. Default's rarity and a similar-sized BBM anomaly for our investment grade subsample turns this hypothetical, enormous, yet rapidly declining risk/liquidity premium into pure fantasy.

Unlike risk or liquidity premia, mispricing can both be distributed unevenly and be large for a small fraction of bonds within BBM's extreme quintiles. Consistency with Figure 2's rapid decay pattern requires only price convergence to fair value within a couple month for such highly mispriced bonds. Finance teaches that savvy traders take advantage of large arbitrage opportunities quickly. The fact that illiquid markets with large trading costs prevent instant price convergence to fair value of small pricing mistakes is no surprise. It takes time for the mispricing of some extreme quintile bonds to build to sufficiently attractive levels to warrant the attention of capital constrained arbitrageurs.

In sum, a few highly mispriced bonds within extreme BBM quintiles can explain Table 3 Panel A's results even when the quintile's remaining bonds trade at prices much closer to fair value. When the trades of savvy market participants force the prices of highly mispriced bonds to converge to fair value, many bonds depart their quintiles. Whether they depart or stay, bonds remaining in the extreme BBM quintile will largely consist of bonds that are close to being fairly valued, rendering a delayed BBM signal useless. As a back of the envelope calculation, if only 10% of the BBM Q5 bonds are underpriced by 3%, and 10% of the Q1 bonds are overpriced by 3%, 50% of these mispriced bonds converging to fair value each month is sufficient to generate a 30 bp alpha (= 3% × 10% / 2 + 3% × 10% / 2) spread with no delay, a 15 bp alpha spread with one-month delay (= 3% × 10% / 4 + 3% × 10% / 4), and a 7.5 bp alpha spread with two-months' delay (= 3% × 10% / 8 + 3% × 10% / 8).

B. Signal Efficacy as a Function of Default Risk and Liquidity

Table 3 Panel A's extensive controls for credit ratings, nearness to default, and liquidity make it unlikely that omitted credit risk or liquidity controls explain the BBM anomaly. Prior YTM discussion, expanded on here, reinforces our credit risk argument. A default prone Q5 bond's YTM should exceed its expected return because payments in default fail to meet the bond contract's promises. The Q5 difference implies that the YTM difference between Q5 and no-default Q1—less than 13 bp in Table 2 Panel A—should also exceed the spread in their risk-related expected returns. Yet, the BBM EW return spread, which averages 44 bp (Table 2 Panel B), is 3.5 times larger than the spread in the extreme quintiles' promised yields. Even with all controls, Table 2 Panel A's 32 bp alpha spread is more than twice the YTM spread.

If BBM merely proxied for inadequate credit risk or liquidity controls, the BBM anomaly should be stronger for bonds that are nearer to default or less liquid. Table 5 adds interaction dummy variables to Table 3 Panel A's regressors. Panel A's interaction terms multiply each BBM quintile dummy or normal score by a dummy for the 20% of bonds that are nearest to default (top half of Panel A) or the 20% with the lowest credit rating (bottom half). Panel B's interaction terms multiply each BBM quintile dummy or normal score by a dummy for the 20% of bonds with the largest bid-ask spread (top of Panel B), 20% lowest trading volume (middle of Panel B), or 20% lowest number of trades (bottom of Panel B). The coefficient on the interaction dummy measures whether the Q5 – Q1 BBM alpha spread is larger for bonds in the top 20% of the default or illiquidity ranking metric. For brevity, Table 5 reports coefficients only for the BBM Q5 dummy and its interaction with the high default- or illiquidity-based dummy.

Each of Table 5 Panel A's 16 specifications exhibit significant BBM Q5 dummy coefficients, implying the BBM anomaly remains for the 80% of bonds least likely to default. However, the coefficients on the interaction dummy are insignificant. For example, in Specification 7 of Panel A's top half, the bonds issued by the quintile of firms nearer to default have a 10 bp per month *lower* alpha spread than the bonds that are further from default. Thus, in all 16 specifications, the 20% of bonds most likely to default have a statistically indistinguishable BBM effect from the rest of the sample, refuting the omitted risk hypothesis.

Table 5 Panel B shows similar findings for illiquidity. All but 2 of BBM's 24 interaction terms with the 20% least liquid bonds are insignificant. The exceptions are the marginally significant volume interaction term in Specifications 2 and 4, implying here that the least liquid bonds exhibit stronger BBM normal score predictability, but only with limited regressor controls. More importantly, each of Panel B's 24 regressions demonstrates that all bonds, irrespective of liquidity quintile, exhibit significant BBM effects. Next, we study whether omitted controls tied to the riskless term structure might explain our findings.

C. BBM and Lower Risk Treasury Notes and Bonds

BBM may also proxy for risk because it better captures duration or related interest rate risk measures that are common to all bonds. However, if this were true, Treasury securities should exhibit a BBM anomaly. Using CRSP's U.S. Treasury Database (excluding T-bills, TIPS and Treasuries with special tax provisions) instead of corporate bonds, Table 6 repeats Table 3 Panel A's regressions with the returns of U.S. Treasury notes and bonds as the dependent variable—dropping regressors that do not apply to Treasuries. Panel A covers the period from July 1961 to December 2019; Panel B covers the period prior to the period we study with TRACE; Panel C studies the return period over which we study corporate bond returns with TRACE—February 2003 to December 2019. The coefficient on the BBM Q5 dummy is insignificant for all specifications and all time periods. By contrast, YTM is a significant predictor of U.S. Treasury returns. This finding is consistent with our controls for duration and term risk being adequate, leaving other risks or, more likely, mispricing as the better explanation for the BBM anomaly in the corporate bond market.

A placebo test, which censors most Treasury transactions, assesses whether our martingale procedure artificially induces a BBM anomaly when trading is infrequent. The censoring forces the transaction pattern in Treasury securities to mimic the distribution of transaction frequencies in the corporate bond market. At the end of each month t, Treasury security j is assigned a randomly selected corporate bond (with replacement) from the universe of corporate bonds that belong to one of our end-of-month t BBM quintiles. If the martingale procedure for the assigned corporate bond employs the bond's last transaction on day d_1 to compute its month t signal, a day d_2 transaction for the beginning price of its month t + 1 return, and a day d_3 transaction for the end price of that return, we compute Treasury security j's month t signal and month t +1 return using the latter security's end-of-day prices from days d_1, d_2, and d_3, respectively. All other transactions in the Treasury security are ignored, forcing it to exhibit the same illiquidity as its assigned corporate bond. We remove observations if day d_1 is before the bond's issuance or day d_3 falls after the bond's maturity date. After making similar assignments to all qualifying Treasury securities in each month, we estimate Table 6 Panel C's regression using the censored Treasury transaction data.

Table 6 Panel D reports the average values for Table 6 Panel C's regression coefficients across 1,000 Monte Carlo simulations. Panel D's results are virtually identical to those in Panel C. For example, with Specification 5, Panel D's coefficient on BBM Q5 is an insignificant 0.039, whereas in Panel C, the BBM Q5 coefficient is –0.014. The similarity of Panels C and D validates the martingale procedure as an appropriate methodology to assess the BBM anomaly when trading is thin. In work not reported in a table, we repeat Table 6 Panel D but randomly perturb the Treasury prices on the three days d_1, d_2, and d_{e3} by a randomly assigned positive or negative 20 bp, each with equal probability. This procedure mimics the impact of a 20 bp half bid-ask spread. Results with the randomly perturbed prices are highly similar.

D. Does BBM Factor Risk Explain the BBM Alpha?

Davis et al. (2000) argue that HML factor betas account for both equity's book-to-market return anomaly and the book-to-market ratio. Here, we construct a bond market version of HML and show that it has only modest ability to diminish the BBM effect. To create an HML-like factor, we parrot Fama and French's (1993) procedure. Each month, we divide bonds into one of six categories based on two bond size categories (market value outstanding) and three BBM categories. Within each of the two bond size categories (large and small), we compute each month's return spread between a value weighting (with weights proportional to each bond's market capitalization) of the top- and bottom-third BBM bonds. Averaging the "large" and "small" bond return spreads generates that month's bond HML factor (BHML).

Table 7 repeats Table 4's time series factor model regressions, adding BHML factor returns. The top half of Table 7 corresponds to Table 4 Panel A (the BBW factor model) and the bottom half corresponds to Table 4 Panel B (the augmented BBW factor model). For brevity, Table 7 only reports intercepts (alphas) and factor betas on BHML. Its rightmost column indicates significant differences in Q5 – Q1 BHML factor beta with both factor models. The first row of the rightmost column also displays a significant alpha spread of 15 bp per month (t = 3.11)—4 bp below Table 4 Panel A's 19 bp spread. Including the term structure factor yields a similar, significant alpha spread (14 bp, t = 3.17). Table 4's alpha reduction is not surprising. If we had constructed the BHML factor as an equal weighting of the top and bottom BBM quintile returns, mathematics would ensure a zero alpha spread. The modestly differing design of BHML similarly leads to a downward bias in the alpha spreads, albeit a less dramatic one. Such a bias makes the significance of the Q5 – Q1 intercepts, even at 14 to 15 bp per month, quite telling. It suggests that it would be conservative to argue that factor risk does not fully explain the BBM anomaly.

IV. Alternative Signals, Junior Bonds, Trading Frequency, and Transaction Costs

We now analyze whether BBM's return predictive ability survives competition with a related mispricing metric, generalizes to a sample that includes junior bonds, or might possibly be generated by off-market prices. It also addresses whether a BBM strategy can be implemented in a cost-effective manner.

A. An Alternative Signal Rooted in Mispricing

We first study whether the BBM signal is simply a crude representation of a mispricing anomaly discovered by BG (2018) for equities. The BG signal, described in Section I.B, can be viewed as a sophisticated BBM signal. In lieu of a single accounting construct, book debt, the BG signal uses predictions from the 28 most commonly reported accounting variables to scale a bond's price. BG (2018) refer to the scaling as a "fair value," obtained as the cross-sectional OLS regression prediction from a set of accounting items. Thus, the BG signal's fair value is simply month t's market-wide norm for the linear function of 28 accounting variables that best explains the aggregate market values of firms' debt. Sorting on the percentage price deviation from the linear prediction is identical to a firm-level sort of the price to fair value ratio. Within each firm, we assign the same BG mispricing percentage to each of its bonds.

Table 8 reports coefficients on some of the key regressors in a pair of FM regressions that mirror Table 3 Panel A's kitchen sink specification. For comparison purposes, Table 8's first column repeats Table 3 Panel A's kitchen sink Specification 7 but narrows the sample to bonds issued by firms that have all of the accounting variables required to compute the BG signal. The second column runs a horse race between the BBM and BG signals by adding BG quintile dummies to the regression. Comparing Specifications 1 and 2 in Table 8's first row indicates that the inclusion of its more sophisticated BG cousin diminishes BBM's alpha negligibly, but BBM remains highly significant, despite the horse race. BBM produces a 29 bp per month alpha spread (t = 3.79) without BG. This drops to 25 bp per month (t = 3.32) when BBM competes with BG, controlling for all the other attributes in Table 3 Panel A's Specification 7.

The relatively small decline in BBM's alpha when the two signals compete indicates that the signals are "marginally quasi-orthogonal." By this, we mean that, controlling for other bond attributes, like YTM, bond credit rating, age, etc., the two signals' remaining randomness is relatively uncorrelated. Table 8's horse race regression thus confirms that BBM is not a proxy for the BG anomaly. If the BG anomaly is the real driver of Table 3 Panel A's findings, we would expect BBM to lose almost all of its return predictive power once we include BG quintile dummies in the regression.

B. BBM's Return Predictive Ability for All Bonds

Prior analysis studied only traditional bonds: senior unsecured bonds with no options other than simple calls. Table 9 repeats Table 3, 4, and 7's regressions, but for all TRACE bonds, including junior and puttable bonds. For brevity, Table 9 Panel A, which parrots Table 3's FM regressions for the all-bond sample, reports selected coefficients of interest; Panel B and C's factor model regressions study EW quintiles using Table 4 and 7's factors, respectively, but report only the intercepts and, for Panel C, BHML betas as well.

Table 9 supplements the traditional sample with corporate bonds that trade less frequently and are riskier than the original sample's senior unsecured bonds. With full controls (Specifications 7 and 8), Table 9 Panel A's results are stronger than those from Table 3 Panel A. For example, the BBM Q5 dummy's coefficient in Specification 7 of Panel A is 38 bp per month (t = 4.26); the corresponding coefficient from Table 3 Panel A Specification 7 is 32 bp (t = 4.05). Likewise, factor model alpha spreads between BBM Q5 and Q1—43 and 48 bp per month for Panel B, 28 and 28 bp per month for Panel C, all significant—exceed those from the traditional sample's factor models, as outlined in Tables 4 and 7, respectively. Thus, the BBM anomaly is stronger for the all-bond sample.

C. Off-Market Prices

TRACE prices that do not reflect mid-market prices could bias inferences if the BBM signal selects time-clustered off-market prices below or above mid-market prices. A burgeoning literature is currently ambiguous about whether dealers offer key customers significantly better or worse prices than others, or whether central dealers offer bid-ask spreads at discounts or premia when providing liquidity in corporate bond markets. For brevity, the arguments below assume key customers get better prices and oligopolistic central dealers offer worse spreads. The arguments merely reverse (e.g., bids become asks, asks become bids, better become worse, higher become lower, etc.) if the off-market prices imply key customers get wider rather than narrower spreads, or cost-efficient central dealers offer narrower rather than wider spreads.

If key customers get better pricing, and the prices of their buy and sell transactions are frequently used to impute TRACE's beginning price for returns in quintiles 1 and 5, customer-dealer transactions would earn higher BBM alpha spreads than dealer-to-dealer return-initiating transactions. Table 10 analyzes this conjecture using Table 3 Panel A's FM regression methodology. It adds interaction terms to the BBM quintile dummies for a return-beginning price that comes from a customer buy or sell transaction. The first column's 0.328 coefficient on BBM quintile 5 represents the Q5 – Q1 alpha spread when a dealer-to-dealer transaction generates the return's beginning price. The interaction term with the customer beginning-price dummy is insignificant in both specifications. This refutes the hypothesis that customer groups receiving favorable off-market bid and ask prices induce spurious BBM correlation with alpha spreads.

The minimum eight-day gap between the signal and the transaction that is used for the return's beginning price ensures that the key customer hypothesis would always be an unlikely explanation for our results. If a high BBM signal (which comes from transactions at both bids and asks) selects bonds that favored customers are buying at the transaction date of the bond return's beginning price, (with the reverse for low BBM signals), the minimum 8-day gap should be sufficient to mitigate the signal's ability to predict the trade direction of specific customer types receiving favored (or disfavored) pricing. Below-market ask prices that inflate both BBM and the return's beginning-of-month price are theoretically possible. However, with an 8-day gap, it seems unlikely to be the source of a 44 bp return spread between Q5 and Q1, let alone the alpha spread observed when controlling for the most recent bid-ask spread.

Further evidence against the favored customer hypothesis comes from shortening the gap, which should greatly increase the extreme quintile spread if favored customers concentrate trades in time intervals of varying length. Instead, the spread decreases, albeit negligibly, to 43 bp, if the gap is reduced by 5 trading days. When we increase the 8-day gap, even by as much as 16–20 trading days, extreme quintile return spreads still exceed 40 bp per month.

The irrelevance of modest gap widening and shortening also helps refute claims that the BBM anomaly is explained by off-market prices transacted with a central dealer offering liquidity at unfavorable terms to its counterparties. According to the central dealer hypothesis, liquidity providing dealers concentrate their trades for periods as long as a month at below-market bid prices for Q5 bonds, and at above-market ask prices for Q1 bonds. As with favored customers, clustering of central dealer trades could inflate Q5 signals and returns, while deflating Q1 signals and returns. For both the key customer and central dealer hypotheses, it is also important that off-market prices persist for no more than 13–15 trading days. A below-market end-of-month bid price for Q5 bonds (typically 13–15 trading day after the beginning-price transaction) would offset the deflated beginning-of-month transaction price, eliminating any bias in returns. Q1 requires a similar caveat. Evidence above showing that gap lengthening by up to 16–20 trading days scarcely affects return spreads is further evidence refuting the off-market price explanation.

D. Buy-and-Hold Returns

Many institutional investors rebalance their bond portfolios infrequently, which reduces the strategy's transaction costs. Table 11 reports factor model alphas (computed as in Table 4) of five yearly rebalanced BBM quintiles and the long-short BBM strategy. These yearly rebalanced BBW and augmented BBW factor models yield extreme quintile alpha spreads of 12 bp (t = 2.05) and 16 bp (t = 2.67) per month, respectively. (To address the issue of statistical inference from 12-month returns that roll over each month, we apply the technique of Jegadeesh and Titman (1993).[17]) This finding suggests that yearly rebalancing approximately halves the BBM strategy's risk-adjusted profits compared to rebalancing monthly.

E. Transaction Costs

BBM's extreme quintile pre-transaction cost alpha spread helps assess market efficiency. However, a BBM anomaly trading strategy is unprofitable if transaction costs exceed gross profits. The corporate bond market's transaction costs are generally high (Chen et al., 2007; Edwards et al., 2007; Bao et al., 2011; Feldhütter, 2012), suggesting BBM signals may not be exploitable by arbitragers as a stand-alone trading strategy.

We use a unique feature of TRACE to first quantify a single homogeneous effective half spread per transacting dollar for every month. For notational simplicity alone, we lag both the return and signal months, and study the transaction cost $T_{q,t}$ from earning the month t return in a BBM quintile q bond. TRACE labels a large proportion of its transactions as customer buys from a dealer or as customer sells

[17] They construct an independent monthly return series that mimics the buy-and-hold outcome. Their 12-month buy-and-hold series equally weighs the same-month returns from twelve partially overlapping strategies that simultaneously buy bonds based on slightly differing signals. Each quintile employs twelve same-quintile indicator signals, differing by signal-delay lags ranging from 0 to 11 months. The technique yields a single monthly return series for each quintile that approximates (due to endpoint months and compounding) the true buy-and-hold quintile portfolio's returns. Time series averaging of the difference between quintile 5 and 1's time series vectors is BBM's buy-and-hold alpha spread.

to a dealer. The label is meaningful because corporate bonds largely trade in dealer over-the-counter markets, and dealers provide all liquidity in these transactions. Transaction cost estimates study all trades in bonds from quintile q (as defined by the BBM signal at the end of month $t-1$) that take place in month t. Each day within the month, we separately compute the average price of customer buys and the average price of customer sells of bonds in that quintile. Equally weighting each day (as opposed to each transaction) yields month t's average buy price and average sell price for quintile q. Subtracting the two monthly averages and dividing by the sum of the two averages yields $T_{q,t}$, the effective month t half spread per dollar of transaction in a quintile q bond. $T_{q,t}$ accurately estimates the bond-type's monthly effective half spread. One of five $T_{q,t}$ values are assigned to each transaction, depending on the bond's quintile assignment.

Returns are affected by the interaction of transaction costs, $T_{q,t}$, with portfolio turnover. Turnover both initiates and concludes each return month. To avoid double-counting, we assign $T_{q,t}$ costs from turnover that would occur (hypothetically) at a month's end to the return in month t. To illustrate, while transactions that generate costs on Friday, May 31, 2013 can be assigned to reduce either the May or June 2013 returns, we assign them to May. Quintile q's end-of-May turnover per dollar of investment is the absolute value of the difference between its portfolio weights assigned at the end of May and those assigned at the end of April, with the latter weights adjusted for the relative returns of the bonds in the quintile portfolio.

In particular, for month t's return, we denote the weight difference as $\mathbf{w}_{q,t+1} - \mathbf{D}_t \mathbf{w}_{q,t}$, where $\mathbf{D}_t$ is an N × N diagonal matrix, with the j-th diagonal element being the month t gross return $(1 + R_{j,t})$ of bond j divided by the month t gross return of BBM quintile portfolio q. $\mathbf{w}_{q,t}$ is an N-vector with each element corresponding to the vector of portfolio weights for quintile q in month t. This weight reflects each bond's (out of the N bonds in our sample) month t (zero or positive but equal) weight assigned by the end of month $t-1$ signal. The beginning-of-month weights change over the course of the month as a result of the bond return $R_{j,t}$—hence the scaling by $\mathbf{D}_t$.[18] Each element of month t's difference vector is assigned one of five half spreads tied to the quintile the bond belongs to throughout month t. If the j-th element of $\mathbf{w}_{q,t+1}$ is positive, bond j is assigned month t's effective half spread for bonds in quintile q. Algebraically, month t's transaction cost per dollar for updating quintile q's portfolio at the end of month t is

$$\mathit{Transaction\,Cost}_{q,t} = \sum_{j\in N}\left| w_{q,t+1}(j) - \frac{w_{q,t}(j)\left(1+R_{j,t}\right)}{\sum_{j\in N} w_{q,t}(j)\left(1+R_{j,t}\right)}\right| \sum_{k=1}^{5} I^{+}\left(w_{k,t+1}(j)\right) T_{k,t}\,, \qquad (4)$$

where N is the universe of bonds in the data set, $I^{+}(x)$ is a {0,1} indicator function that takes on the value

[18] If an element of $\mathbf{D}_t$ is lacking because the bond matured, has yet to be issued, or did not trade, the corresponding portfolio weight will be zero and we treat the product of the missing $\mathbf{D}_t$ element and the weight as zero.

of 1 only if x is strictly positive, and v(j) is element j of any vector **v**, corresponding to bond j. Subtracting this cost from month t's quintile q's return produces a month t return net of transaction costs.

While dealers meeting customer liquidity needs execute on the profitable side of the bid-ask midpoint, customers can bilaterally negotiate prices with a dealer. As a result, transaction costs for corporate bonds may depend on the type of investor, the type of trade, and the relative market power dealers have over the customer. Consistent with this thesis, Bao et al. (2011) show that corporate bond transaction costs are larger for small transactions. To account for the potential heterogeneity across investors, we compute the transaction cost measure described above for two alternative sets of transactions. The first set includes all dealer-to-customer transactions in our sample of TRACE-sourced bonds, while the second is limited to dealer-to-customer transactions with volumes of at least 100,000 U.S. dollars. The latter subset of observations likely captures trades that have lower transaction costs due to larger customers' greater bargaining power with dealers (a phenomenon documented by Bessembinder et al., 2009). Figure 3 graphs the monthly bid-ask spreads for all trades (Panel A) and for large trades (Panel B). It displays the equal-weighted average of bid-ask spreads for an equal weighting of all quintiles as well as for bonds in the first and fifth quintiles. The overall bid-ask spread patterns are fairly consistent with the findings of Choi and Huh (2019). Not surprisingly, costs spiked during the 2008–2009 financial crisis.

Table 12 reports average portfolio turnover and transaction costs as well as gross and net performance for trades restricted to the extreme BBM quintiles. Net performance is the intercept from regressing quintile portfolio excess returns net of monthly transaction costs on factors. Subtracting transaction costs monthly alters factor betas, so Table 12's net performance is not exactly equal to the difference between Table 4 and Table 11's average gross alpha and average transaction costs. Panel A and B's alpha columns reproduce Table 4 and 11's monthly and yearly rebalanced factor model alphas, respectively. With monthly rebalancing, the long-short BBM strategy has a pre-transaction-cost (i.e., gross) BBW factor model alpha of 19 bp per month. The transaction cost associated with its turnover of 31% amounts to 50 bp for all investors,[19] which exceeds the alpha spreads computed for the strategy. Even applying the (more than 50%) lower transaction costs of 19 bp for large transactions to the same gross alpha offers no consolation, yielding an insignificant 2 bp per month net alpha. Augmented BBW factor model alphas net of transactions costs are an insignificant 7 bp per month for large transactions.

Buy-and-hold (i.e., yearly rebalanced) strategies are designed to reduce turnover, which is borne out in Panel B with turnover of 7% and monthly transactions costs of 11 bp and 4 bp for all investors and

[19] One-way turnover in month t is calculated as the sum of the portfolio weights of the bonds that leave the portfolio in month $t + 1$, accounting for the sales. Transaction costs are calculated following equation (4), which accounts for two-way turnover including both purchases and sales.

institutions (i.e., trade size of 100,000 U.S. dollars or more), respectively. While these strategies also earn lower risk-adjusted gross profits due to alpha decay, all buy-and-hold alphas net of transaction costs are positive. BBW 5-factor net profit for all customer trades are still insignificant, but the augmented BBW model indicates significant net profits of 12 bp (t = 2.06). Thus, the buy-and-hold variation of the strategy survives the transaction costs incurred by larger trades, typically initiated by institutions, enhancing overall net performance. While institutions may also face additional short sales costs and constraints, these can be avoided when merely tilting long-only portfolios towards underpriced and away from overpriced bonds.

V. Conclusion

Fundamental differences between the corporate bond and equity markets could have ramifications for the relative efficiency of these two financial markets. The corporate bond market may be relatively more efficient because a more sophisticated institutional investor base dominates its trading (Chordia et al., 2017). It also may be less efficient due to its differing, over-the-counter market structure. Over-the-counter trading likely engenders greater transaction costs and less pre-trade price transparency, preventing arbitrageurs from correcting mispricing. Corporate bonds also tend to trade with less liquidity than stocks and are held for long periods by their primary investors: pension funds, insurance companies, endowments, and mutual funds. Even if mispriced, however, bonds' finite maturity may force rapid convergence to fair prices.

To aid understanding of the corporate bond market's informational efficiency, this paper studies book-to-market's role in the pricing of corporate bonds. Alpha spreads between extreme BBM quintile portfolios—32 bp per month with the most extensive controls—are sizable considering the low volatility of corporate bond returns compared to stock returns. Like equity book-to-market, small bonds exhibit larger BBM alphas, perhaps indicating more efficient pricing of larger bond issues.

The paper presents evidence that the BBM trading strategy's alpha is unlikely to stem from omitted risk, microstructure, or liquidity controls. This leaves mispricing, particularly for small-issue bonds, as the best explanation for the BBM anomaly. Supporting this explanation is the pattern of profits with BBM signal delay, calibrations from yield spreads, similar BBM signal efficacy for bonds with more default risk, less liquidity, or bonds hedged with own firm equity, the irrelevance of callability and market microstructure controls, and the inability of BBW factor betas to explain BBM profits, even with an additional HML-like bond factor. Moreover, the riskless term structure cannot explain the BBM anomaly, as BBM does not predict U.S. Treasury returns—even when artificially forcing Treasury transactions data to mimic the sparseness of corporate bond transactions.

We emphasize that our results are conservative. Trades are from signals that become known at least eight days prior to the start of the trade month, and we compute returns from intra-month transaction prices, eschewing "end-of-month" WRDS bond returns. This lengthens the time between signal and implementation by an average of about half a month. In addition, most of our focus is on senior unsecured bonds with, at best, simple call options (for which call exercise offers little economic advantage). This bond class exhibits negligible default risk in our sample, even more so for the investment grade bonds in the class, which exhibit a similarly strong BBM anomaly. When we analyze a larger set of TRACE bonds that includes junior bonds, alpha spreads are considerably larger. Finally, our application the martingale assumption to compute returns from the prices of intra-month transactions effectively assumes that bonds with no trades or one trade have smaller spreads than they actually do. All of these assumptions, as well as tax considerations, argue for higher BBM spreads than we report.

It is not entirely surprising that the convergence of some corporate bond prices to their fair values is the more plausible explanation for the alpha generated by the BBM anomaly. Bond trading faces greater trading and liquidity frictions than several other asset classes, which allows deviations from fair value to exist initially. Indeed, transaction costs, which we estimate for different transaction sizes, are sufficiently high to deter arbitrageurs who would otherwise profit from the anomaly's monthly rebalancing signal. However, institutional strategies with lower turnover, like one-year buy-and-hold strategies, do earn significant risk-adjusted profits even net of transaction costs. Moreover, long-term investors, who incur transaction costs anyway, benefit from knowing which bonds have the highest and lowest risk-adjusted returns. Their decisions to trade mispriced bonds could be the source of the relatively rapid convergence to fair value that we believe is the source of the observed BBM alpha.

The BBM anomaly's mispricing explanation may explain book-to-market effects for other asset classes. If bonds, which have adequate risk controls, favor a mispricing explanation for BBM's effect, mispricing becomes a more likely explanation for book-to-market anomalies in other asset classes, like equity, where risk controls are harder to come by. Consistent with the equity mispricing explanation is the decline in equity HML since 2002 as equity trading frictions declined and the equity book-to-market anomaly became more widely known in hedge fund circles. Frictions, particularly information frictions, are greater for assets with small market capitalizations. In this light, the similarly higher degree of book-to-market efficacy for both small stocks and small-issue bonds is intriguing.

Bond book-to-market ratios are highly negatively correlated with bond prices. While quintile sorts on bond prices also predict returns, BBM is a better return predictor. The differences are not striking, however, and it would be acceptable to believe that the difference between a bond price anomaly and a bond book-to-market anomaly is semantic. For equities, this is largely the case as well. It is just that an equity share is an arbitrary way to scale a price, making equity book-to-market a less noisy mispricing metric than share price. Of course, this assumes that both the bond and equity book-to-market premia stem from the same source: mispricing. However, given the many price-related anomalies in the equity literature, including book-to-market, their anomalies could plausibly stem from the same phenomenon.

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Figure 1: Transaction Timing of Prices Used for Signal and Returns

The figure shows hypothetical examples of how bond transactions are used to construct the signal and monthly bond returns. In particular, the bond price P^S in month t used to construct the signal is at least one week prior to the end of month t. To construct the bond return in month $t + 1$, we use the first price of the bond in month $t + 1$ as the beginning price P^B and the last bond price in month $t + 1$ as the end price P^E.

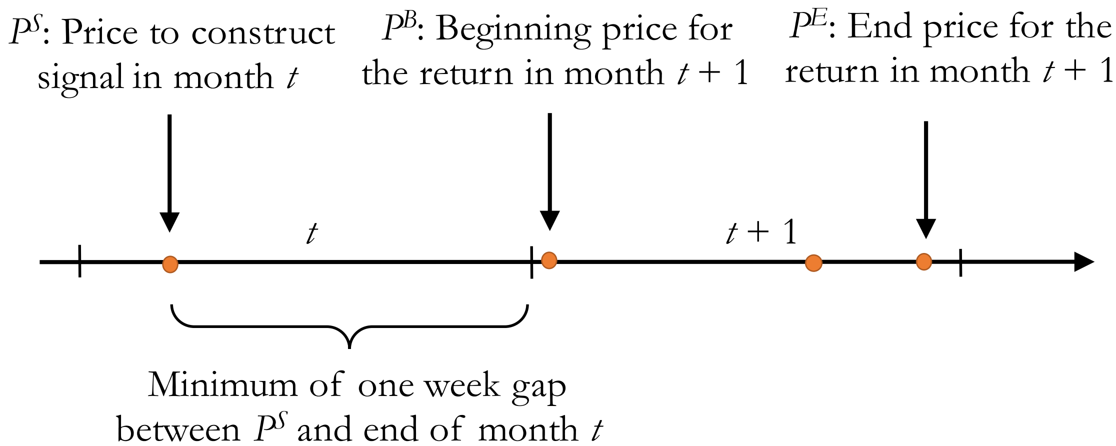


Figure 2: Signal Delay

The figure shows average coefficients from Fama and MacBeth (1973) regressions of monthly bond returns on bond book-to-market, controlling for other bond and equity characteristics (Specification (7) in Table 3 Panel A). Book-to-market quintile dummies lagged by one to twelve months. The table employs quintile dummies for quintiles 2, 3, 4, and 5 of each characteristic as regressors, but the figure displays only the coefficient on the quintile 5 dummy for bond book-to-market.

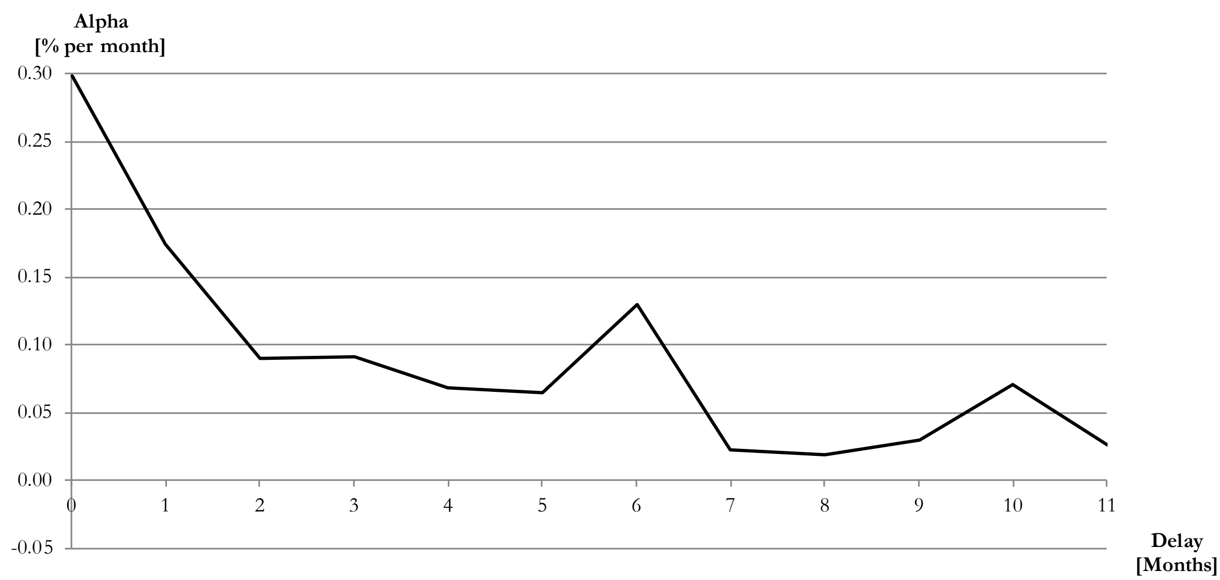
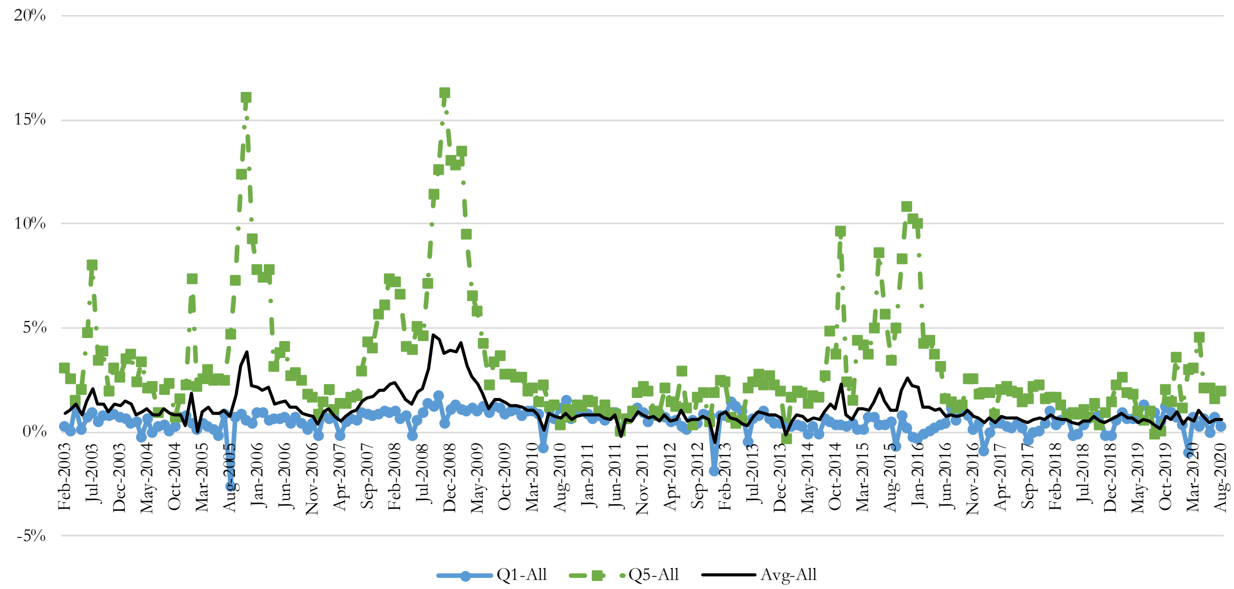


Figure 3: Monthly Bid-Ask Spreads for Bond Book-to-Market Quintiles

The figure shows monthly bid-ask spreads by bond book-to-market quintiles, separately for all transactions (Panel A) and institutional transactions (Panel B). Every day, we take the average of buy transactions and sell transactions for all bonds in each quintile. We take the average of daily prices in a month separately for buys and sells, and compute the quintile-level bid-ask spreads from the average buys and sells for the month. The figure shows the spreads for quintile 1 (lowest BBM), quintile 5 (highest BBM) and the average of all quintiles.

Panel A: All Transactions



Panel B: Institutional Transactions

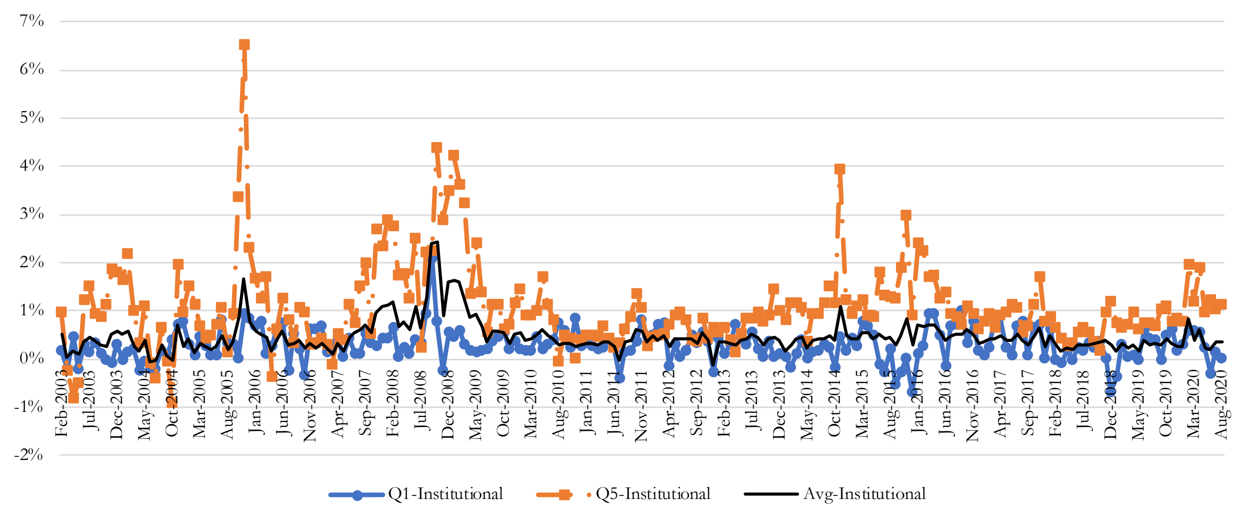


Table 1: Summary Statistics

The table reports statistics on the offering price of corporate bonds (Panel A), and the time difference between the transaction dates of the bond prices P^S used to construct the bond book-to-market signal in month t and bond prices used as beginning of month prices P^B to construct bond returns in month $t + 1$ (Panel B). Panel A reports the distribution of offering prices per $100 of face value, separately for the sample of senior, unsecured bonds ("Traditional Bonds") and all bonds including junior bonds or bonds with embedded options ("All Bonds"). Panel B reports the difference in calendar days between the transaction date for beginning-of-month price in month $t + 1$ (used to construct the bond's return in month $t + 1$) and the transaction date for month-t trading signal. Statistics are computed using bond-level panel data, separately for traditional bonds as well as all bonds. The return sample period is February 2003 to September 2020.

Panel A: Offering Price Statistics

				Percentiles									
	N	Mean	Minimum	1	5	10	25	50	75	90	95	99	Maximum
Traditional Bonds	8,925	99.6	40.8	97.3	98.7	99.1	99.5	99.8	99.9	100.0	100.0	100.0	106.9
All Bonds	12,643	99.6	25.0	97.6	98.9	99.2	99.6	99.9	100.0	100.0	100.0	100.0	112.6

Panel B: Time Difference Between Trading Signals and Bond Return

			Percentiles								
	N	Mean	1	5	10	25	50	75	90	95	99
Traditional Bonds	458,139	15.9	8.0	8.0	8.0	9.0	11.0	14.0	26.0	37.0	88.0
All Bonds	565,093	19.3	8.0	8.0	8.0	9.0	11.0	18.0	34.0	51.0	133.0

Table 2: Portfolio Sorts by Bond Book-to-Market

The table reports summary statistics of bond and firm characteristics by bond book-to-market (BBM) quintiles (Panel A), averages and selected test statistics of monthly portfolio returns from intra-month prices (Panel B), averages of monthly portfolio returns and current yields from inter-month prices by number of month $t+1$ trades (Panel C), and statistics on beginning and end prices for returns (Panel D). Panel A's numbers are time series averages of equal weightings of each month's characteristics across all observations ("All"), observations for each BBM quintile (Q1, …, Q5) that month, and each month's cross-sectional correlation of BBM with the characteristic ("Correlation"). Panel B reports time series averages of each month's equal- and value-weighted returns, the return spread between the BBM Q5 and Q1 portfolios, as well as the fraction of positive BBM Q5 – Q1 return spreads. It reports results separately for all bonds, as well as bonds below ("Small Bonds") and above ("Large Bonds") the monthly median bond value from sequential sorts on BBM and then bond value. Panel C's first three rows report equally weighted average monthly returns, separately for all observations, as well as for bonds that trade never or only once in month $t+1$. Returns are based on Panel B's formula, found in the text, except that the price transacted just prior to the trade date of month-t's signal's price is month $t+1$ return's beginning-of-month price, the price first transacted after month $t+1$ is the return's ending price, and the price change is scaled by the number of months (including fractional months) between the price pair. Panel C's bottom row reports the current yield (per month) of one-trade bonds. Panel D reports the fraction of beginning and end prices for returns at bids, asks, and from dealer-to-dealer transactions by BBM quintiles. The fractions are scaled so that they sum to 100% for each quintile. The sample consists of nonfinancial firms with U.S. dollar-denominated, senior unsecured corporate bonds without embedded options other than call options.

Panel A: Bond and Firm Characteristics

			Bond Book/Market (BBM) Quintiles				
	All	Correlation	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)
Bond Book/Market	0.963	1.00	0.845	0.923	0.961	0.994	1.094
Bond Mispricing	-0.001	0.29	-0.011	-0.005	-0.001	0.003	0.011
Bond Coupon Rate	5.513	-0.30	6.818	5.866	5.321	4.744	4.816
Bond Yield	4.779	0.42	4.682	4.218	4.341	4.469	6.191
Bond Credit Spread	1.579	0.35	1.466	1.300	1.325	1.230	2.571
Bond Value	532.2	-0.10	610.7	564.3	522.3	508.4	455.2
Bond Face Value	501.7	-0.03	508.0	517.5	500.2	503.2	479.8
Bond Age	4.870	-0.16	7.268	5.083	4.373	3.702	3.926
Bond Maturity	11.18	-0.10	16.41	10.184	8.832	8.445	12.02
Bond Duration	6.984	-0.14	9.388	6.666	5.924	5.688	7.248
Bond Rating	8.159	0.24	7.462	7.901	8.144	8.173	9.126
Bond Reversal	0.685	-0.05	0.814	0.706	0.665	0.639	0.662
Bond Momentum	3.421	-0.22	4.548	3.752	3.354	2.935	2.871
Bond Volume	49.23	0.10	33.08	40.35	47.66	56.20	68.86
Bond Volume Institutions	47.93	0.09	32.45	39.10	46.18	54.68	67.25
Number of Trades	103.1	0.14	56.94	93.42	111.1	118.9	135.1
Number of Trades Institutions	30.66	0.13	18.93	26.15	30.97	35.31	41.93
Bond Bid/Ask Spread	0.495	0.19	0.470	0.436	0.447	0.469	0.682
Bond Bid/Ask Spread Institutions	0.198	0.14	0.205	0.181	0.179	0.181	0.258
Number of Bonds Oustanding	37.90	0.00	37.83	30.81	32.75	39.84	48.30
Number of Days from Beginning of Month	2.907	-0.08	3.899	2.843	2.602	2.587	2.741
Number of Days from End of Month	2.743	-0.08	3.727	2.714	2.478	2.413	2.508
Nearness to Default	-9.488	0.17	-10.10	-9.77	-9.479	-9.490	-8.605
Investment Grade	0.863	-0.24	0.954	0.910	0.869	0.854	0.726
Non-Investment Grade	0.137	0.24	0.046	0.090	0.131	0.146	0.274
Offering Price	99.49	0.05	99.23	99.49	99.55	99.61	99.56
Equity Mispricing	0.080	0.00	0.049	0.074	0.088	0.080	0.129
Equity Market Capitalization	2,720	-0.06	48,318	39,548	40,351	45,811	39,560
Equity Book/Market	0.652	0.20	0.591	0.601	0.604	0.640	0.825
Equity Beta	0.979	0.16	0.891	0.925	0.963	0.987	1.127
SUE	-0.003	-0.10	0.001	0.001	0.000	0.000	-0.016
Gross Profitability	0.226	-0.04	0.230	0.232	0.231	0.228	0.212
Earnings Yield	0.012	-0.28	0.056	0.053	0.047	0.038	-0.134
Equity Short-term Reversal	1.028	-0.03	1.067	1.061	1.051	1.053	0.910
Equity Momentum	10.59	-0.14	13.27	12.22	11.73	10.46	5.269
Equity Long-term Reversal	54.19	-0.10	58.54	58.03	56.28	54.01	44.13
Accruals	0.098	-0.03	0.093	0.105	0.112	0.107	0.077

(continued)

Table 2: Portfolio Sorts by Bond Book-to-Market (continued)

Panel B: Average Portfolio Returns

				Bond Book/Market (BBM) Quintiles					Q5-Q1 (high BBM - low BBM)			
		All	Correlation	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)	Fraction > 0	*p-value*	Average	*t-stat*
All Bonds	Equal-weighted Bond Return (t+1)	0.660	0.04	0.566	0.544	0.576	0.655	1.011	0.63	[0.00]	0.444	[3.86]
	Value-weighted Bond Return (t+1)	0.572	0.04	0.526	0.500	0.530	0.584	0.934	0.59	[0.01]	0.408	[3.58]
Small Bonds	Equal-weighted Bond Return (t+1)	0.798	0.04	0.660	0.621	0.675	0.776	1.170	0.61	[0.00]	0.511	[3.42]
Large Bonds	Equal-weighted Bond Return (t+1)	0.557	0.04	0.494	0.483	0.502	0.568	0.905	0.60	[0.00]	0.411	[3.67]

Panel C: Scaled Monthly Portfolio Returns from Inter-Month Transactions and One-Trade Bond Current Yield

Number of Tades					Bond Book/Market (BBM) Quintiles					Q5-Q1 (high BBM - low BBM)			
in Month t + 1		All	Correlation	Obs.	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)	Fraction > 0	*p-value*	Average	*t-stat*
Any	Equal-weighted Bond Return (t+1)	0.576	0.06	517,353	0.510	0.495	0.481	0.505	0.889	0.58	[0.65]	0.379	[3.09]
Zero	Equal-weighted Bond Return (t+1)	0.450	0.09	64,705	0.363	0.385	0.296	0.267	0.902	0.54	[10.86]	0.539	[2.51]
One	Equal-weighted Bond Return (t+1)	0.511	0.04	5,512	0.340	0.377	0.703	0.694	0.611	0.57	[3.68]	0.268	[2.35]
	Equal-weighted Current Yield (t+1)	0.450	-0.24	5,512	0.469	0.454	0.428	0.418	0.441	0.24	[99.98]	-0.040	[-2.05]

Panel D: Fraction of Beginning and End Prices for Returns at Bids and Ask

Beginning Price of Bond	End Price of Bond	Bond Book/Market (BBM) Quintiles				
Return in t + 1	Return in t + 1	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)
Ask	Ask	9.4%	9.4%	10.2%	11.1%	12.0%
Ask	Bid	10.7%	9.4%	9.0%	9.1%	9.3%
Ask	Dealer	5.9%	6.4%	6.8%	7.3%	7.6%
Bid	Ask	12.8%	13.0%	13.4%	13.5%	12.5%
Bid	Bid	16.1%	15.0%	13.8%	12.9%	12.3%
Bid	Dealer	10.2%	11.0%	10.9%	10.6%	9.6%
Dealer	Ask	9.4%	10.1%	10.8%	11.5%	12.2%
Dealer	Bid	13.9%	12.8%	11.8%	11.1%	11.2%
Dealer	Dealer	11.6%	12.9%	13.2%	12.9%	13.2%

Table 3: Fama-MacBeth Cross-Sectional Regressions

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics and control variables. Across different specifications, returns are regressed against prior month values for bond book-to-market, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. Panel A employs quintile dummies for the characteristics as regressors except for bond book-to-market in even-numbered specifications, which employ the normal score of bond book-to-market. Each month's quintiles are determined from sorts of bonds with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for quintiles 2, 3, 4, and 5 of each characteristic, but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. Panel B shows results for various robustness tests. Panel B Specification (1) uses parametric versions of the control variables, while Specifications (2)–(6) use non-parametric controls as in Panel A. Panel B Specification (2) uses the monthly bond return from trader marks provided by Merrill Lynch as dependent variable, while Specification (3) uses Merrill Lynch data to construct both the monthly bond return as well as bond book-to-market. In Panel B Specification (4), the regressand is an unbiased estimate of each bond's equity hedged return using the equity of the bond issuer. We estimate hedge ratios as the predictions of hedonic panel regressions of each bond's return on interactions between the monthly equity return of the bond issuer in excess of LIBOR and 131 dummies representing the bond's 61 (non-collinear) characteristics, including 38 industry dummies. The bond return component from flat prices is rescaled to alleviate biases from thin trading. The dependent variable in Panel B Specification (5) is the equity return of the bond's issuing firm. Panel B Specification (6) uses the same regression model as Panel A Specification (7), but restricts the sample to bonds that are investment grade ("Investment Grade Bonds"). The table shows average coefficients and test statistics as well as the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

(continued)

Table 3: Fama-MacBeth Cross-Sectional Regressions (continued)

Panel A: Baseline Model

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Bond Book/Market Q5	0.441	[3.62] ***			0.445	[3.64] ***			0.265	[3.21] ***			0.320	[4.05] ***		
Bond Book/Market (normal score)			0.139	[3.13] ***			0.140	[3.15] ***			0.096	[2.25] **			0.117	[3.13] ***
Bond Characteristic Controls																
Bond Coupon Rate Q5									0.011	[0.16]	0.055	[0.67]	0.046	[0.74]	0.095	[1.25]
Bond Yield Q5									0.416	[5.78] ***	0.427	[5.96] ***	0.433	[6.11] ***	0.446	[6.27] ***
Bond Credit Spread Q5									0.042	[0.64]	0.016	[0.26]	0.046	[0.69]	0.028	[0.44]
Bond Value Q5									-0.049	[-0.89]	-0.036	[-0.66]	-0.070	[-1.43]	-0.056	[-1.16]
Bond Age Q5									0.035	[0.87]	0.031	[0.75]	0.006	[0.14]	0.003	[0.07]
Bond Maturity Q5									0.122	[0.64]	0.107	[0.59]	0.110	[0.61]	0.094	[0.54]
Bond Duration Q5									0.129	[0.73]	0.157	[0.94]	0.108	[0.64]	0.139	[0.87]
Bond Bid/Ask Spread Q5									0.076	[1.90] *	0.070	[1.86] *	0.070	[1.83] *	0.066	[1.78] *
Bond Reversal Q5									-0.010	[-0.26]	-0.012	[-0.30]	-0.029	[-0.78]	-0.028	[-0.76]
Bond Momentum Q5									0.005	[0.11]	0.002	[0.04]	-0.026	[-0.58]	-0.027	[-0.63]
Bond Rating Q5									-0.242	[-3.35] ***	-0.259	[-3.77] ***	-0.219	[-2.61] ***	-0.242	[-2.97] ***
Nearness to Default Q5									-0.010	[-0.19]	-0.017	[-0.33]	0.041	[0.54]	0.040	[0.54]
Stock Characteristic Controls																
Beta Q5													0.028	[0.37]	0.012	[0.16]
Market Capitalization Q5													0.038	[0.54]	0.037	[0.52]
Book/Market Q5													-0.003	[-0.04]	0.000	[0.00]
Short-term Reversal Q5													0.281	[4.42] ***	0.280	[4.47] ***
Momentum Q5													-0.004	[-0.06]	0.003	[0.05]
Long-term Reversal Q5													-0.011	[-0.19]	0.000	[0.00]
Accruals Q5													-0.068	[-1.20]	-0.077	[-1.40]
SUE Q5													0.126	[2.40] **	0.131	[2.54] **
Gross Profitability Q5													0.186	[2.39] **	0.186	[2.42] **
Earnings Yield Q5													0.045	[0.67]	0.050	[0.77]
Market Microstructure Controls																
Number of Bonds in t+1					0.000	[-0.45]	0.000	[0.07]	0.000	[-0.63]	0.000	[-0.79]	0.000	[-1.12]	0.000	[-0.97]
Percent of Bond Market Cap Traded in t+1					-0.182	[-1.66] *	-0.137	[-1.18]	-0.169	[-2.02] **	-0.164	[-2.04] **	-0.186	[-1.83] *	-0.178	[-1.81] *
Number of Days from Beginning of Month t+1					0.005	[1.74] *	0.007	[2.13] **	0.002	[0.74]	0.002	[0.79]	0.001	[0.31]	0.001	[0.43]
Number of Days from End of Month t+1					0.015	[4.24] ***	0.016	[4.68] ***	0.012	[3.47] ***	0.012	[3.65] ***	0.010	[3.03] ***	0.011	[3.17] ***
Intercept	0.5244	[3.35] ***	0.620	[3.86] ***	0.643	[3.41] ***	0.695	[3.60] ***	0.481	[3.04] ***	0.540	[3.55] ***	-0.239	[-0.55]	-0.208	[-0.46]
Observations	1,149		1,149		1,149		1,149		1,149		1,149		1,149		1,149	
Adj. R-Squared	0.11		0.10		0.12		0.11		0.25		0.25		0.28		0.29	
Industry Control	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

(continued)

Table 3: Fama-MacBeth Cross-Sectional Regressions (continued)

Panel B: Robustness

				Non-Parametric Controls														
	(1)			(2)			(3)			(4)			(5)			(6)		
	Regressions with Parametric Controls			Bond Return (Merrill Lynch)			BBM and Bond Return (Merrill Lynch)			BondReturn – HedgeRatio * (StockReturn - Libor)			Stock Return			Investment Grade Bonds		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Bond Book/Market Q5	0.292	[4.52]	***	0.202	[2.52]	**	0.495	[5.03]	***	0.316	[4.82]	***	-0.082	[-0.71]		0.307	[5.97]	***
Bond Characteristic Controls																		
Bond Coupon Rate	0.028	[1.68]	*	-0.018	[-0.27]		0.093	[1.31]		0.058	[1.10]		-0.203	[-1.71]	*	0.141	[2.94]	***
Bond Yield	0.102	[2.48]	**	0.333	[4.46]	***	0.206	[2.88]	***	0.448	[6.32]	***	-0.252	[-1.54]		0.324	[4.88]	***
Bond Credit Spread	-0.034	[-1.09]		0.075	[1.00]		0.137	[1.78]	*	0.031	[0.46]		-0.054	[-0.41]		0.045	[0.69]	
Bond Value	0.000	[0.21]		0.006	[0.09]		0.060	[1.48]		-0.060	[-1.27]		-0.037	[-0.50]		-0.078	[-1.52]	
Bond Age	0.005	[1.19]		-0.050	[-1.07]		0.015	[0.33]		0.001	[0.03]		0.154	[1.95]	*	0.078	[1.68]	*
Bond Maturity	0.006	[0.85]		0.226	[0.97]		0.025	[0.11]		0.061	[0.32]		0.482	[1.25]		0.047	[0.30]	
Bond Duration	-0.009	[-0.42]		-0.072	[-0.36]		0.174	[0.79]		0.099	[0.57]		-0.207	[-0.51]		0.174	[1.24]	
Bond Bid/Ask Spread	0.059	[2.42]	**	0.038	[1.10]		0.002	[0.06]		0.065	[1.72]	*	-0.147	[-2.47]	**	0.033	[1.14]	
Bond Reversal	-0.010	[-1.50]		0.059	[1.55]		0.028	[0.71]		-0.020	[-0.54]		0.068	[0.97]		-0.092	[-2.24]	**
Bond Momentum	-0.004	[-0.76]		-0.072	[-1.39]		-0.050	[-1.10]		-0.014	[-0.35]		0.144	[1.24]		-0.068	[-1.78]	*
Bond Rating	-0.034	[-3.56]	***	-0.011	[-0.10]		-0.073	[-0.67]		-0.189	[-2.48]	**	-0.334	[-1.26]		-0.128	[-1.69]	*
Nearness to Default	0.011	[1.68]	*	-0.084	[-1.05]		-0.093	[-1.08]		0.029	[0.36]		0.458	[1.58]		0.004	[0.06]	
Stock Characteristic Controls																		
Beta	-0.011	[-0.29]		0.105	[1.33]		0.093	[1.27]		0.056	[0.78]		-0.145	[-0.45]		-0.064	[-0.89]	
Market Capitalization	0.002	[0.14]		0.109	[1.31]		0.082	[1.05]		0.029	[0.47]		0.054	[0.21]		0.000	[0.00]	
Book/Market	-0.041	[-1.79]	*	-0.026	[-0.30]		-0.084	[-1.03]		-0.003	[-0.04]		-0.016	[-0.06]		-0.059	[-0.88]	
Short-term Reversal	0.012	[6.15]	***	0.260	[3.45]	***	0.269	[3.50]	***	0.347	[5.14]	***	-0.498	[-2.08]	**	0.123	[2.31]	**
Momentum	0.001	[2.26]	**	0.108	[1.33]		0.113	[1.37]		0.092	[1.63]		-0.511	[-1.61]		-0.079	[-1.29]	
Long-term Reversal	0.000	[-0.97]		-0.179	[-2.48]	**	-0.081	[-1.27]		0.045	[0.80]		-0.097	[-0.39]		-0.057	[-0.97]	
Accruals	0.027	[0.75]		-0.026	[-0.39]		-0.006	[-0.08]		-0.042	[-0.75]		-0.195	[-1.04]		0.000	[0.00]	
SUE	0.250	[0.62]		-0.020	[-0.38]		-0.016	[-0.29]		0.128	[2.14]	**	-0.129	[-0.64]		0.024	[0.45]	
Gross Profitability	-0.138	[-1.73]	*	0.167	[1.48]		0.157	[1.60]		0.145	[1.90]	*	0.224	[0.71]		0.187	[2.20]	**
Earnings Yield	0.246	[1.35]		0.048	[0.71]		-0.010	[-0.18]		0.083	[1.25]		-0.203	[-0.96]		0.056	[0.92]	
Market Microstructure Controls																		
Number of Bonds in $t+1$	0.000	[-2.10]	**	0.000	[-0.68]		0.000	[-0.27]		0.000	[-0.60]		0.000	[-0.40]		0.000	[-0.06]	
Percent of Bond Market Cap Traded in $t+1$	-0.151	[-1.80]	*	-0.124	[-0.87]		-0.199	[-1.39]		-0.145	[-1.48]		-0.286	[-0.83]		-0.009	[-0.09]	
Number of Days from Beginning of Month $t+1$	0.004	[1.35]		-0.003	[-1.05]		-0.001	[-0.32]		0.001	[0.20]		-0.003	[-0.62]		0.002	[0.54]	
Number of Days from End of Month $t+1$	0.012	[3.35]	***	-0.003	[-0.86]		0.000	[0.05]		0.011	[3.20]	***	0.000	[0.02]		0.015	[4.35]	***
Intercept	0.269	[1.10]		0.083	[0.19]		-1.290	[-0.88]		-0.560	[-1.25]		2.417	[2.22]	**	0.846	[1.27]	
Observations	1,139			664			838			1,149			1,169			1,007		
Adj. R-Squared	0.31			0.53			0.53			0.26			0.58			0.28		
Industry Control	Yes			Yes			Yes			Yes			Yes			Yes		

Table 4: Factor Model Time Series Regressions

The table shows results from time series regressions of monthly portfolio returns (in excess of 1-month USD LIBOR) on bond factor models. Bonds are sorted each month into quintiles based on bond book-to-market (BBM) and combined into equal-weighted or value-weighted portfolios. The table reports intercepts, slope coefficients, *t*-statistics, the number of observations, and R-squared separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the return spreads between the highest bond book-to-market (Q5) and lowest bond book-to-market (Q1) quintiles. Regressors for the BBW (2019) factor model in Panel A are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model in Panel B further adds a term structure factor, constructed from independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. The difference in returns between these two extreme maturity quintiles is our term structure factor. Panel C shows intercepts of equal-weighted portfolios for the BBW factor model and the augmented BBW factor model separately for small and large bonds (from sequential sorts on BBM and size based on the median monthly bond value). In addition, it shows results using a 21-factor model listed in Appendix A. Standard errors are estimated using the Newey West (1987) procedure. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: BBW Factor Model

	Q1 (low BBM)		Q2		Q3		Q4		Q5 (high BBM)		Q5-Q1 (high - low BBM)	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Equal-weighted portfolios												
Intercept	0.207	[2.92] ***	0.153	[2.72] ***	0.173	[4.48] ***	0.185	[4.76] ***	0.400	[4.63] ***	0.193	[2.17] **
Bond Market Factor (*t*+1)	0.829	[6.56] ***	0.834	[8.90] ***	0.792	[16.90] ***	0.875	[20.49] ***	0.908	[9.44] ***	0.078	[0.64]
Bond Value at Risk Factor (*t*+1)	0.044	[0.76]	-0.054	[-0.98]	-0.085	[-2.43] **	-0.172	[-6.80] ***	-0.135	[-2.30] **	-0.180	[-1.94] *
Bond Rating Factor (*t*+1)	-0.139	[-3.30] ***	-0.071	[-2.63] ***	-0.068	[-3.80] ***	-0.036	[-2.63] ***	0.213	[5.01] ***	0.352	[4.91] ***
Bond Illiquidity Factor (*t*+1)	-0.257	[-1.66] *	-0.173	[-1.11]	-0.113	[-1.25]	0.013	[0.24]	0.153	[2.37] **	0.411	[2.19] **
Bond Reversal Factor (*t*+1)	-0.024	[-0.51]	0.013	[0.35]	0.042	[1.82] *	0.060	[2.45] **	-0.019	[-0.49]	0.006	[0.10]
R-Squared	0.74		0.82		0.89		0.88		0.79		0.60	
Observations	212		212		212		212		212		212	
Value-weighted portfolios												
Intercept	0.149	[2.26] **	0.093	[2.16] **	0.085	[2.99] ***	0.080	[2.45] **	0.272	[3.42] ***	0.123	[1.44]
Bond Market Factor (*t*+1)	0.985	[8.35] ***	0.936	[12.59] ***	0.927	[33.94] ***	1.010	[25.90] ***	1.061	[11.70] ***	0.077	[0.61]
Bond Value at Risk Factor (*t*+1)	0.060	[1.22]	-0.088	[-2.18] **	-0.131	[-4.66] ***	-0.202	[-6.18] ***	-0.167	[-2.55] **	-0.226	[-2.42] **
Bond Rating Factor (*t*+1)	-0.190	[-4.33] ***	-0.108	[-5.05] ***	-0.110	[-7.82] ***	-0.070	[-3.88] ***	0.146	[3.21] ***	0.336	[4.38] ***
Bond Illiquidity Factor (*t*+1)	-0.292	[-2.55] **	-0.130	[-1.19]	-0.041	[-0.72]	0.053	[0.99]	0.155	[1.10]	0.447	[2.12] **
Bond Reversal Factor (*t*+1)	-0.063	[-1.46]	-0.006	[-0.19]	0.032	[1.72] *	0.042	[1.82] *	0.012	[0.24]	0.074	[1.17]
R-Squared	0.80		0.88		0.94		0.93		0.82		0.58	
Observations	212		212		212		212		212		212	

(continued)

Table 4: Factor Model Time Series Regressions (continued)

Panel B: Augmented BBW Factor Model

	Q1 (low BBM)			Q2			Q3			Q4			Q5 (high BBM)			Q5-Q1 (high - low BBM)		
	Coef	*t* -stat		Coef	*t* -stat		Coef	*t* -stat		Coef	*t* -stat		Coef	*t* -stat		Coef	*t* -stat	
Equal-weighted portfolios																		
Intercept	0.128	[2.38]	**	0.122	[2.45]	**	0.158	[4.59]	***	0.181	[4.75]	***	0.358	[4.35]	***	0.230	[2.55]	**
Bond Market Factor (*t* +1)	0.639	[5.76]	***	0.761	[8.45]	***	0.755	[14.49]	***	0.864	[18.83]	***	0.807	[6.58]	***	0.167	[1.13]	
Bond Value at Risk Factor (*t* +1)	-0.092	[-1.54]		-0.107	[-1.70]	*	-0.112	[-2.52]	**	-0.180	[-5.00]	***	-0.208	[-3.10]	***	-0.116	[-1.53]	
Bond Rating Factor (*t* +1)	-0.070	[-1.76]	*	-0.045	[-1.62]		-0.055	[-2.44]	**	-0.032	[-1.69]	*	0.250	[4.30]	***	0.320	[3.86]	***
Bond Illiquidity Factor (*t* +1)	-0.062	[-0.42]		-0.098	[-0.62]		-0.075	[-0.81]		0.024	[0.45]		0.257	[3.45]	***	0.320	[1.72]	*
Bond Reversal Factor (*t* +1)	-0.013	[-0.30]		0.018	[0.47]		0.044	[1.86]	*	0.061	[2.42]	**	-0.013	[-0.33]		0.000	[0.00]	
Bond Term Structure Factor (*t* +1)	0.255	[5.40]	***	0.099	[2.77]	***	0.050	[1.74]	*	0.015	[0.50]		0.136	[1.93]	*	-0.120	[-1.42]	
R-Squared	0.79			0.83			0.90			0.88			0.80			0.61		
Observations	212			212			212			212			212			212		
Value-weighted portfolios																		
Intercept	0.059	[1.33]		0.064	[1.78]	*	0.073	[2.95]	***	0.079	[2.56]	**	0.236	[3.06]	***	0.177	[2.11]	**
Bond Market Factor (*t* +1)	0.764	[7.91]	***	0.865	[12.71]	***	0.898	[25.00]	***	1.009	[21.60]	***	0.972	[9.27]	***	0.208	[1.55]	
Bond Value at Risk Factor (*t* +1)	-0.099	[-2.06]	**	-0.139	[-2.80]	***	-0.152	[-4.31]	***	-0.203	[-5.28]	***	-0.231	[-3.16]	***	-0.132	[-1.61]	
Bond Rating Factor (*t* +1)	-0.110	[-2.76]	***	-0.082	[-3.67]	***	-0.100	[-5.46]	***	-0.070	[-3.23]	***	0.178	[3.14]	***	0.288	[3.43]	***
Bond Illiquidity Factor (*t* +1)	-0.066	[-0.66]		-0.057	[-0.54]		-0.011	[-0.19]		0.054	[0.94]		0.247	[1.71]	*	0.312	[1.48]	
Bond Reversal Factor (*t* +1)	-0.049	[-1.35]		-0.001	[-0.05]		0.034	[1.72]	*	0.042	[1.81]	*	0.017	[0.35]		0.066	[1.08]	
Bond Term Structure Factor (*t* +1)	0.297	[6.30]	***	0.095	[2.81]	***	0.039	[1.62]		0.001	[0.06]		0.120	[2.27]	**	-0.177	[-2.52]	**
R-Squared	0.85			0.88			0.94			0.93			0.83			0.60		
Observations	212			212			212			212			212			212		

(continued)

Table 4: Factor Model Time Series Regressions (continued)

Panel C: Robustness

	Q1 (low BBM)			Q2			Q3			Q4			Q5 (high BBM)			Q5-Q1 (high - low BBM)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
BBW Factor Model																		
Small Bonds	0.339	[4.29]	***	0.263	[3.64]	***	0.312	[5.69]	***	0.343	[5.20]	***	0.608	[4.67]	***	0.269	[2.21]	**
Large Bonds	0.113	[1.57]		0.072	[1.57]		0.069	[2.16]	**	0.067	[1.97]	**	0.261	[3.17]	***	0.148	[1.59]	
Augmented BBW Factor Model																		
Small Bonds	0.275	[4.01]	***	0.231	[3.49]	***	0.294	[5.84]	***	0.331	[5.05]	***	0.553	[4.99]	***	0.277	[2.56]	**
Large Bonds	0.021	[0.41]		0.041	[1.03]		0.052	[1.91]	*	0.066	[2.07]	**	0.225	[2.82]	***	0.204	[2.22]	**
21-Factor Model	0.198	[3.52]	***	0.178	[5.26]	***	0.202	[6.71]	***	0.197	[5.47]	***	0.377	[5.30]	***	0.179	[2.38]	**

Table 5: Default Risk and Liquidity Interactions

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics with BBM interaction variables for bonds with 20% high default risk (Panel A) or 20% low liquidity (Panel B). In Panel A, in addition to the regressors employed in Table 3 Panel A, all regressions include the fifth quintile dummy for nearness to default (top) or bond credit rating (bottom), as well as interactions of these worst credit indicator variables with the four quintile dummies for bond book-to-market (odd-numbered columns) or normal score of bond book-to-market (even-numbered columns), respectively. In Panel B, all regressions include the fifth quintile dummy for bid/ask spread (top), the negative of volume (middle), or the negative of the number of trades (bottom), as well as interactions of these illiquidity indicator variables with the four quintile dummies for bond book-to-market (odd-numbered columns) or normal score of bond book-to-market (even-numbered columns), respectively. Volume and the number of trades are multiplied by minus one so that the fifth quintile of all three liquidity measures identify bonds with the lowest degree of liquidity. The table shows average coefficients and test statistics as well as the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Default Risk

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Nearness to Default																
Bond Book/Market Q5 * Nearness to Default Q5	-0.047	[-0.30]			-0.023	[-0.15]			-0.071	[-0.48]			-0.100	[-0.73]		
Bond Book/Market (normal score) * Nearness to Default Q5			0.111	[1.29]			0.114	[1.32]			0.047	[0.63]			0.080	[1.12]
Bond Book/Market Q5	0.397	[3.82] ***			0.396	[3.77] ***			0.278	[4.04] ***			0.317	[4.31] ***		
Bond Book/Market (normal score)			0.103	[2.90] ***			0.106	[2.95] ***			0.095	[3.22] ***			0.107	[3.80] ***
Nearness to Default Q5	0.019	[0.16]	-0.039	[-0.52]	0.011	[0.09]	-0.035	[-0.47]	-0.009	[-0.09]	-0.097	[-1.90] *	0.101	[0.82]	-0.043	[-0.51]
Observations	1,149		1,149		1,149		1,149		1,149		1,149		1,149		1,149	
Adj. R-Squared	0.13		0.13		0.14		0.14		0.26		0.26		0.29		0.29	
Bond Characteristic Controls (see Table 3)	No		No		No		No		Yes		Yes		Yes		Yes	
Stock Characteristic Controls (see Table 3)	No		No		No		No		No		No		Yes		Yes	
Market Microstructure Controls (see Table 3)	No		No		Yes		Yes		Yes		Yes		Yes		Yes	
Industry Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Bond Rating																
Bond Book/Market Q5 * Bond Rating Q5	-0.036	[-0.26]			-0.032	[-0.23]			-0.100	[-0.78]			-0.006	[-0.05]		
Bond Book/Market (normal score) * Bond Rating Q5			0.084	[0.89]			0.086	[0.91]			0.031	[0.37]			0.082	[1.11]
Bond Book/Market Q5	0.411	[3.96] ***			0.411	[3.93] ***			0.275	[4.06] ***			0.293	[4.08] ***		
Bond Book/Market (normal score)			0.108	[3.09] ***			0.111	[3.13] ***			0.096	[3.30] ***			0.102	[3.62] ***
Bond Rating Q5	-0.088	[-0.92]	-0.070	[-0.84]	-0.075	[-0.80]	-0.063	[-0.76]	-0.201	[-2.18] **	-0.306	[-3.70] ***	-0.222	[-2.51] **	-0.314	[-3.46] ***
Observations	1,149		1,149		1,149		1,149		1,149		1,149		1,149		1,149	
Adj. R-Squared	0.14		0.14		0.14		0.14		0.26		0.26		0.29		0.29	
Bond Characteristic Controls (see Table 3)	No		No		No		No		Yes		Yes		Yes		Yes	
Stock Characteristic Controls (see Table 3)	No		No		No		No		No		No		Yes		Yes	
Market Microstructure Controls (see Table 3)	No		No		Yes		Yes		Yes		Yes		Yes		Yes	
Industry Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

(continued)

Table 5: Default Risk and Liquidity Interactions (continued)

Panel B: Liquidity

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Bond Bid-Ask Spread																
Bond Book/Market Q5 * Bid/Ask Spread Q5	0.037	[0.29]			0.046	[0.36]			-0.003	[-0.03]			0.027	[0.28]		
Bond Book/Market (normal score) * Bid/Ask Spread Q5			0.065	[1.13]			0.068	[1.22]			0.027	[0.60]			0.036	[0.90]
Bond Book/Market Q5	0.365	[3.12] ***			0.368	[3.12] ***			0.252	[3.40] ***			0.295	[3.86] ***		
Bond Book/Market (normal score)			0.101	[2.48] **			0.102	[2.50] **			0.097	[2.77] ***			0.111	[3.51] ***
Bid/Ask Spread Q5	0.157	[2.67] ***	0.204	[4.32] ***	0.152	[2.64] ***	0.196	[4.15] ***	0.081	[1.48]	0.041	[1.23]	0.062	[1.07]	0.038	[1.07]
Observations	1,149		1,149		1,149		1,149		1,149		1,149		1,149		1,149	
Adj. R-Squared	0.13		0.12		0.13		0.13		0.26		0.26		0.29		0.29	
Bond Characteristic Controls (see Table 3)	No		No		No		No		Yes		Yes		Yes		Yes	
Stock Characteristic Controls (see Table 3)	No		No		No		No		No		No		Yes		Yes	
Market Microstructure Controls (see Table 3)	No		No		Yes		Yes		Yes		Yes		Yes		Yes	
Industry Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Bond Volume																
Bond Book/Market Q5 * Bond Volume Q5	0.091	[1.13]			0.081	[0.95]			0.011	[0.13]			-0.025	[-0.31]		
Bond Book/Market (normal score) * Bond Volume Q5			0.067	[2.10] **			0.065	[1.93] *			0.045	[1.41]			0.026	[0.84]
Bond Book/Market Q5	0.394	[3.28] ***			0.401	[3.31] ***			0.262	[3.09] ***			0.306	[3.73] ***		
Bond Book/Market (normal score)			0.127	[2.91] ***			0.129	[2.93] ***			0.105	[2.34] **			0.124	[2.99] ***
Bond Volume Q5	0.112	[2.32] **	0.169	[5.08] ***	0.063	[1.31]	0.120	[3.99] ***	-0.002	[-0.03]	0.031	[0.76]	-0.031	[-0.57]	-0.002	[-0.05]
Observations	1,383		1,383		1,383		1,383		1,383		1,383		1,383		1,383	
Adj. R-Squared	0.10		0.10		0.11		0.10		0.22		0.23		0.25		0.25	
Bond Characteristic Controls (see Table 3)	No		No		No		No		Yes		Yes		Yes		Yes	
Stock Characteristic Controls (see Table 3)	No		No		No		No		No		No		Yes		Yes	
Market Microstructure Controls (see Table 3)	No		No		Yes		Yes		Yes		Yes		Yes		Yes	
Industry Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Number of Trades																
Bond Book/Market Q5 * Number of Trades Q5	0.021	[0.25]			0.006	[0.07]			-0.034	[-0.46]			-0.032	[-0.44]		
Bond Book/Market (normal score) * Number of Trades Q5			0.008	[0.25]			0.000	[0.00]			0.000	[0.00]			-0.005	[-0.20]
Bond Book/Market Q5	0.412	[3.28] ***			0.412	[3.27] ***			0.272	[3.15] ***			0.312	[3.75] ***		
Bond Book/Market (normal score)			0.141	[3.05] ***			0.141	[3.02] ***			0.115	[2.51] **			0.133	[3.14] ***
Number of Trades Q5	0.075	[1.81] *	0.120	[4.43] ***	-0.002	[-0.06]	0.025	[0.91]	-0.063	[-1.29]	-0.046	[-1.33]	-0.091	[-1.80] *	-0.064	[-1.81] *
Observations	1,383		1,383		1,383		1,383		1,383		1,383		1,383		1,383	
Adj. R-Squared	0.10		0.09		0.10		0.10		0.22		0.23		0.25		0.25	
Bond Characteristic Controls (see Table 3)	No		No		No		No		Yes		Yes		Yes		Yes	
Stock Characteristic Controls (see Table 3)	No		No		No		No		No		No		Yes		Yes	
Market Microstructure Controls (see Table 3)	No		No		Yes		Yes		Yes		Yes		Yes		Yes	
Industry Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

Table 6: Treasury Bonds

The table shows results from Fama-MacBeth (1973) regressions of monthly Treasury bond returns on Treasury bond characteristics. Treasury bond returns are regressed on bond book-to-market (BBM), coupon rate, yield to maturity, market value, age, time to maturity, duration, bid-ask spreads, lagged returns, and cumulative returns from $t-6$ to $t-1$ of Treasury bonds. The regressions include dummy variables for quintiles 2, 3, 4, and 5 of each characteristic, but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. Panels A to C use all daily observations to construct monthly returns, while in Panel D, we randomly match each Treasury security that is used in a BBM quintile in a month to a corporate bond. We then use the signal date, beginning-of-month date and end-of-month date for the matching corporate bond to calculate BBM for the Treasury security, and run regressions using this simulated data set. We simulate the data 1,000 times, and report the average of the coefficients, *t*-statistics, adjusted R-squared, and number of observations across simulations in Panel D. The table also shows the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)		(2)		(3)		(4)		(5)	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Panel A. 1961.7-2019.12										
Bond Book/Market Q5	-0.068	[-1.34]	-0.021	[-0.76]					-0.029	[-1.31]
Bond Coupon Rate Q5			0.026	[0.97]			0.003	[0.11]	-0.011	[-0.58]
Bond Yield Q5					0.283	[3.53] ***	0.223	[4.48] ***	0.194	[4.26] ***
Bond Value Q5			-0.042	[-1.38]			-0.055	[-2.49] **	-0.018	[-1.64] *
Bond Age Q5			-0.012	[-0.29]			-0.056	[-1.85] *	-0.045	[-1.73] *
Bond Maturity Q5			0.124	[1.20]			0.019	[0.69]	0.023	[0.92]
Bond Duration Q5			0.039	[2.17] **			0.009	[0.86]	0.01	[0.96]
Bond Bid/Ask Spread Q5			0.015	[0.74]			0.007	[0.46]	0.006	[0.36]
Bond Reversal Q5			-0.082	[-2.05] **			-0.075	[-2.41] **	-0.073	[-2.41] **
Bond Momentum Q5			-0.026	[-1.19]			0.021	[0.87]	-0.016	[-0.92]
Intercept	0.577	[9.11] ***	0.605	[7.95] ***	0.376	[9.80] ***	0.416	[7.81] ***	0.512	[9.40] ***
Observations	148		148		148		148		148	
Adj. R-Squared	0.29		0.78		0.58		0.78		0.79	
Panel B. 1961.7-2003.1										
Bond Book/Market Q5	-0.050	[-0.89]	-0.026	[-0.75]					-0.039	[-1.51]
Bond Coupon Rate Q5			0.016	[0.45]			-0.011	[-0.39]	-0.033	[-1.57]
Bond Yield Q5					0.210	[2.46] **	0.253	[4.29] ***	0.224	[4.19] ***
Bond Value Q5			-0.056	[-1.21]			-0.075	[-2.33] **	-0.019	[-1.17]
Bond Age Q5			0.026	[0.43]			-0.050	[-1.36]	-0.024	[-0.93]
Bond Maturity Q5			0.093	[1.24]			0.024	[0.76]	0.018	[0.60]
Bond Duration Q5			0.024	[1.45]			0.001	[0.08]	0.000	[-0.04]
Bond Bid/Ask Spread Q5			0.01	[0.42]			0.007	[0.38]	0.000	[-0.02]
Bond Reversal Q5			-0.088	[-1.67] *			-0.071	[-1.88] *	-0.076	[-2.05] **
Bond Momentum Q5			-0.049	[-1.65] *			0.024	[0.74]	-0.030	[-1.40]
Intercept	0.635	[9.44] ***	0.761	[7.35] ***	0.472	[9.02] ***	0.494	[6.88] ***	0.631	[8.76] ***
Observations	117		117		117		117		117	
Adj. R-Squared	0.28		0.73		0.52		0.74		0.73	

(continued)

Table 6: Treasury Bonds (continued)

	(1)		(2)		(3)		(4)		(5)	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Panel C. 2003.2-2019.12										
Bond Book/Market Q5	-0.113	[-1.03]	-0.011	[-0.25]					-0.014	[-0.32]
Bond Coupon Rate Q5			0.052	[1.41]			0.036	[0.98]	0.044	[1.21]
Bond Yield Q5					0.463	[2.55] **	0.080	[1.49]	0.057	[0.86]
Bond Value Q5			-0.016	[-1.23]			-0.013	[-1.09]	-0.018	[-1.41]
Bond Age Q5			-0.083	[-1.52]			-0.067	[-1.28]	-0.081	[-1.47]
Bond Maturity Q5			0.167	[0.73]			0.011	[0.24]	0.030	[0.70]
Bond Duration Q5			0.076	[1.62]			0.029	[1.51]	0.035	[1.78] *
Bond Bid/Ask Spread Q5			0.025	[0.64]			0.008	[0.26]	0.018	[0.46]
Bond Reversal Q5			-0.070	[-1.23]			-0.081	[-1.54]	-0.068	[-1.28]
Bond Momentum Q5			0.020	[0.75]			0.014	[0.50]	0.015	[0.55]
Intercept	0.432	[3.01] ***	0.22	[3.71] ***	0.137	[5.69] ***	0.226	[4.39] ***	0.218	[3.67] ***
Observations	225		225		225		225		225	
Adj. R-Squared	0.30		0.89		0.73		0.88		0.89	
Panel D. 2003.2-2019.12, Simulated data accounting for infrequent transactions										
Bond Book/Market Q5	-0.099	[-1.02]	0.041	[0.76]					0.039	[0.72]
Bond Coupon Rate Q5			0.121	[2.30] **			0.099	[1.95] *	0.119	[2.23] **
Bond Yield Q5					0.360	[2.45] **	0.176	[1.35]	0.165	[1.22]
Bond Value Q5			-0.029	[-1.18]			-0.022	[-0.92]	-0.026	[-1.06]
Bond Age Q5			-0.061	[-1.02]			-0.056	[-1.00]	-0.058	[-0.95]
Bond Maturity Q5			-0.017	[-0.10]			0.033	[0.51]	0.020	[0.32]
Bond Duration Q5			0.053	[1.02]			0.025	[0.63]	0.026	[0.64]
Bond Bid/Ask Spread Q5			0.013	[0.34]			0.007	[0.21]	0.013	[0.34]
Bond Reversal Q5			-0.053	[-0.77]			-0.049	[-0.74]	-0.047	[-0.72]
Bond Momentum Q5			-0.020	[-0.30]			-0.036	[-0.53]	-0.033	[-0.49]
Intercept	0.411	[3.41] ***	0.180	[2.18] **	0.171	[9.46] ***	0.196	[3.10] ***	0.161	[1.89] *
Observations	201		201		201		201		201	
Adj. R-Squared	0.21		0.51		0.44		0.50		0.51	

Table 7: Factor Model Time Series Regressions with Bond HML Factor

The table shows results from time series regressions of monthly portfolio returns (in excess of 1-month USD LIBOR) on bond factor models augmented with a high-minus-low factor based on bond book-to-market (BHML). Bonds are sorted each month into quintiles based on bond book-to-market and combined into equal-weighted portfolios. The table reports intercepts, slope coefficients, t-statistics, the number of observations, and R-squared separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the corresponding times-series of return spreads between the highest book-to-market (Q5) and lowest book-to-market (Q1) bond quintiles. To form the Bond HML factor, each month, we divide bonds into one of 6 categories based on bond size (market value outstanding) and bond book-to-market. For the 3 categories in the larger of the two bond sizes (bottom, middle, and top third of month t bond book-to-market), we compute the spread in the month $t + 1$ value-weighted bond returns (based on bond value outstanding) between the top and bottom third of bond book-to-market bonds. We then repeat the exercise for the bonds in the smaller of the two bond sizes. We then average the two value-weighted return spreads and include the average as the BHML factor. Regressors for the BBW (2019) factor model are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model further adds a term structure factor. Standard errors are estimated using the Newey West (1987) procedure. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1 (low BBM)			Q2			Q3			Q4			Q5 (high BBM)			Q5-Q1 (high - low BBM)		
	Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat	
BBW Factor Model																		
Intercept	0.23	[4.34]	***	0.169	[4.61]	***	0.177	[5.18]	***	0.183	[4.63]	***	0.380	[4.58]	***	0.150	[3.11]	***
BHML Factor (t+1)	-0.580	[-9.33]	***	-0.423	[-5.45]	***	-0.111	[-1.74]	*	0.068	[1.79]	*	0.505	[5.00]	***	1.085	[15.06]	***
R-Squared	0.848			0.89			0.90			0.88			0.83			0.86		
Observations	212			212			212			212			212			212		
5 Factors (see Table 4 Panel A)	Yes			Yes			Yes			Yes			Yes			Yes		
Augmented BBW Factor Model																		
Intercept	0.171	[4.29]	***	0.157	[4.74]	***	0.166	[5.70]	***	0.174	[4.66]	***	0.309	[4.48]	***	0.138	[3.17]	***
BHML Factor (t+1)	-0.512	[-8.78]	***	-0.408	[-4.87]	***	-0.097	[-1.40]		0.078	[2.08]	**	0.587	[5.35]	***	1.100	[15.11]	***
R-Squared	0.87			0.89			0.90			0.88			0.84			0.87		
Observations	212			212			212			212			212			212		
6 Factors (see Table 4 Panel B)	Yes			Yes			Yes			Yes			Yes			Yes		

Table 8: BG's Bond Mispricing Signal vs. Bond Book-to-Market Signal

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics, including bond book-to-market and bond mispricing. Bond mispricing measures deviations of a firm's aggregate debt obligations $V_{i,t}$ from predictions based on its accounting variables. Each month t, we cross-sectionally regress $V_{i,t}$ on firm i's 28 most commonly reported items from Compustat's point-in-time accounting database. The regression predictions represent month t peer-implied norms for each firm's total liabilities. Each bond is then assigned the BG signal of its issuing firm, which is the percentage deviation of the firm's predicted $V_{i,t}$ from its actual value. Across different specifications, returns are regressed against prior month values for bond book-to-market, bond mispricing, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The table employs quintile dummies for the characteristics as regressors. Each month's quintiles are determined from sorts of bonds with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for quintiles 2, 3, 4, and 5 of each characteristic but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) on bond book-to-market and bond mispricing for brevity. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. The table shows average coefficients and test statistics as well as the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)			(2)		
	Coef	t-stat		Coef	t-stat	
Bond Book/Market Q5	0.287	[3.79]	***	0.245	[3.32]	***
Bond Mispricing Q5				0.202	[2.94]	***
Observations	1,014			1,014		
Adj. R-Squared	0.31			0.32		
Bond Characteristic Controls (see Table 3)	Yes			Yes		
Stock Characteristic Controls (see Table 3)	Yes			Yes		
Market Microstructure Controls (see Table 3)	Yes			Yes		
Industry Controls	Yes			Yes		

Table 9: Sample of All Corporate Bonds

The table shows results for regressions using the sample of all bonds including junior bonds and bonds with embedded options. Panel A shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics for the same regression specifications as in Table 3 Panel A. The regressions include dummy variables for quintiles 2, 3, 4, and 5 of each characteristic, but the panel displays only the coefficients of the quintile dummy with the largest amount of book-to-market (Q5) or the normal score of bond book-to-market for brevity. The panel also shows average coefficients and test statistics as well as the average number of observations and average adjusted R-squared. Panel B shows results from time series regressions of monthly equal-weighted portfolio returns (in excess of 1-month USD LIBOR) on bond factor models as in Table 4. For brevity, the panel only displays coefficients and *t*-statistics for the regression intercept as well as the number of observations and R-squared. Panel C shows results from time series regressions of monthly equal-weighted portfolio returns (in excess of 1-month USD LIBOR) on a risk model augmented with a high-minus-low factor based on bond book-to-market (BHML), following Table 7. The panel reports intercepts, slope coefficients, *t*-statistics, the number of observations, and R-squared separately for each of the five portfolios, Q1–Q5, and for the return spreads between the highest bond book-to-market (Q5) and lowest bond book-to-market (Q1) quintiles. For brevity, the panel only displays coefficients and *t*-statistics for the regression intercept and the BHML factor as well as the number of observations and R-squared. Standard errors are estimated using the Newey West (1987) procedure. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fama-MacBeth Cross-Sectional Regressions

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Bond Book/Market Q5	0.575	[4.79] ***			0.569	[4.72] ***			0.336	[3.64] ***			0.384	[4.26] ***		
Bond Book/Market (normal score)			0.192	[4.28] ***			0.189	[4.19] ***			0.152	[3.47] ***			0.171	[4.22] ***
Observations	1,315		1,315		1,315		1,315		1,315		1,315		1,315		1,315	
Adj. R-Squared	0.11		0.10		0.12		0.11		0.23		0.24		0.26		0.26	
Bond Characteristic Controls (see Table 3)	No		No		No		No		Yes		Yes		Yes		Yes	
Stock Characteristic Controls (see Table 3)	No		No		No		No		No		No		Yes		Yes	
Market Microstructure Controls (see Table 3)	No		No		Yes		Yes		Yes		Yes		Yes		Yes	
Industry Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

(continued)

Table 9: Sample of All Corporate Bonds (continued)

Panel B: Factor Model Time-Series Regressions

	Q1 (low BBM)			Q2			Q3			Q4			Q5 (high BBM)			Q5-Q1 (high - low BBM)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
BBW Factor Model																		
Intercept	0.203	[3.11]	***	0.219	[3.91]	***	0.308	[6.76]	***	0.473	[8.29]	***	0.636	[6.82]	***	0.433	[5.13]	***
R-Squared	0.77			0.82			0.86			0.76			0.82			0.65		
Observations	212			212			212			212			212			212		
5 Factors (see Table 4 Panel A)	Yes			Yes			Yes			Yes			Yes			Yes		
Augmented BBW Factor Model																		
Intercept	0.137	[2.60]	**	0.187	[3.86]	***	0.300	[6.90]	***	0.464	[8.78]	***	0.616	[6.77]	***	0.478	[5.67]	***
R-Squared	0.80			0.83			0.86			0.76			0.82			0.67		
Observations	212			212			212			212			212			212		
6 Factors (see Table 4 Panel B)	Yes			Yes			Yes			Yes			Yes			Yes		

Panel C: Factor Model Time-Series Regressions with Bond HML Factor

	Q1 (low BBM)			Q2			Q3			Q4			Q5 (high BBM)			Q5-Q1 (high - low BBM)		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
BBW Factor Model																		
Intercept	0.269	[5.11]	***	0.261	[6.27]	***	0.310	[7.46]	***	0.447	[8.12]	***	0.547	[7.16]	***	0.278	[5.70]	***
BHML Factor (*t*+1)	-0.397	[-6.16]	***	-0.251	[-3.06]	***	-0.016	[-0.24]		0.155	[2.81]	***	0.530	[3.40]	***	0.927	[8.36]	***
R-Squared	0.83			0.86			0.86			0.77			0.87			0.88		
Observations	212			212			212			212			212			212		
5 Factors (see Table 4 Panel A)	Yes			Yes			Yes			Yes			Yes			Yes		
Augmented BBW Factor Model																		
Intercept	0.212	[5.25]	***	0.235	[7.44]	***	0.302	[8.00]	***	0.428	[8.89]	***	0.495	[7.96]	***	0.283	[6.25]	***
BHML Factor (*t*+1)	-0.351	[-5.04]	***	-0.230	[-2.59]	**	-0.009	[-0.14]		0.170	[2.86]	***	0.573	[3.32]	***	0.924	[7.86]	***
R-Squared	0.85			0.86			0.86			0.77			0.87			0.88		
Observations	212			212			212			212			212			212		
6 Factors (see Table 4 Panel B)	Yes			Yes			Yes			Yes			Yes			Yes		

Table 10: Off-Market Prices

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics. BBM quintile dummies have interaction variables for dealer-customer bond transactions with the omitted dummy reflecting a dealer-to-dealer transaction. In addition, the regression includes the control variables used in Specification (7) of Table 3 Panel A. The table employs quintile dummies for the characteristics as regressors except for bond book-to-market in specification (2), which employs the normal score of bond book-to-market. All regressions include an indicator variable for customer transactions, defined as cases where the beginning bond price used to construct the return in month $t + 1$ comes from a customer transaction. The customer transaction indicator is also interacted with the quintiles and the normal score for bond book-to-market. The table shows average coefficients and test statistics of selected regressors as well as the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)			(2)		
	Coef	t-stat		Coef	t-stat	
Customer Transaction	0.006	[0.24]		0.019	[1.00]	
BondBookToMarketQ2 * Customer Transaction	0.017	[0.51]				
BondBookToMarketQ3 * Customer Transaction	0.019	[0.53]				
BondBookToMarketQ4 * Customer Transaction	0.041	[1.21]				
BondBookToMarketQ5 * Customer Transaction	-0.018	[-0.31]				
Bond Book/Market (normal score) * Customer Transaction				0.005	[0.23]	
Bond Book/Market Q5	0.328	[4.69]	***			
Bond Book/Market (normal score)				0.101	[3.18]	***
Observations	1,104			1,104		
Adj. R-Squared	0.27			0.28		
Bond Characteristic Controls (see Table 3)	Yes			Yes		
Stock Characteristic Controls (see Table 3)	Yes			Yes		
Market Microstructure Controls (see Table 3)	Yes			Yes		
Industry Controls	Yes			Yes		

Table 11: Buy-and-Hold Returns

The table shows results from time series regressions of monthly bond portfolio returns (in excess of 1-month USD LIBOR) on risk factors. Following Jegadeesh and Titman (1993, 2001), the table measures the monthly performance of a portfolio held for 12 months with the following non-overlapping returns methodology: Bonds are sorted each month into 12 sets of quintiles based on bond book-to-market (BBM) that is delayed from 0 to 11 months and combined into equal-weighted portfolios within the same signal delay cohort. The monthly return that is used in the regression equally weights the twelve portfolios that belong to the same quintile. The table reports intercepts and associated *t*-statistics separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the corresponding times-series of return spreads between the highest book-to-market (Q5) and lowest book-to-market (Q1) bond quintiles. Regressors for the BBW (2019) factor model are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model further adds a term structure factor. Standard errors are estimated using the Newey West (1987) procedure. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1 (low BBM)			**Q2**			**Q3**			**Q4**			**Q5 (high BBM)**			**Q5-Q1 (high - low**		
	Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat		Coef	*t*-stat	
Alpha BBW Factor Model	0.208	[3.11]	***	0.151	[2.83]	***	0.165	[4.54]	***	0.195	[5.23]	***	0.332	[4.75]	***	0.124	[2.05]	**
Alpha Augmented BBW Factor Model	0.141	[2.63]	***	0.117	[2.43]	**	0.148	[4.51]	***	0.182	[5.77]	***	0.298	[4.72]	***	0.157	[2.67]	***

Table 12: Turnover and Transaction Costs

The table shows monthly one-way turnover, transaction costs, as well as gross and net performance of the long-short investment strategy based on bond book-to-market for alternatively monthly rebalancing (Panel A) and 12-month buy-and-hold strategies (Panel B). Results are reported separately for the returns of the portfolios of the lowest bond book-to-market bonds (Q1), the highest bond book-to-market bonds (Q5) and the spread portfolio (Q5–Q1). Separately for the BBW factor model and the Augmented BBW factor model, the first column reproduces the factor alphas from Tables 4 and 11, respectively. Regressors for the BBW (2019) factor model are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model further adds a term structure factor. The second column reports one-way turnover (in percent per month). Columns 3-6 report the average transaction costs based on two-way turnover and transaction cost adjusted (net) performance as the intercept of a regression of quintile portfolio returns (in excess of 1-month USD LIBOR) minus monthly transaction costs on the risk factors. Standard errors are estimated using the Newey West (1987) procedure. Daily average bid and ask prices are computed by taking the average of all dealer buy and dealer sell transactions for all bonds in a quintile. We then take the average of daily bids and asks in a month separately for bids and asks, and compute monthly bid-ask spreads. We assign these quintile-level half spreads to bonds that join the quintile, and calculate transaction costs as in Eq. (4). As shown in the column headings, the bid-ask spreads are calculated alternatively for all transactions in TRACE (All) and transactions with volume at least 100,000 U.S. dollars (Institutions). The return sample period is February 2003 to September 2020.

			All				Institutions			
Portfolio	Alpha	One-Way Turnover	Transaction Costs	Net Performance	t-stat		Transaction Costs	Net Performance	t-stat	
Panel A: Monthly Rebalancing										
BBW Factor Model										
Q1	0.207	12%	0.085	0.282	[3.75]	***	0.045	0.250	[3.35]	***
Q5	0.400	19%	0.410	0.032	[0.34]		0.147	0.270	[3.13]	***
Q5-Q1	0.193	31%	0.495	-0.250	[-2.46]	**	0.192	0.020	[0.22]	
Augmented BBW Factor Model										
Q1	0.128	12%	0.085	0.198	[3.65]	***	0.045	0.165	[3.08]	***
Q5	0.358	19%	0.410	-0.004	[-0.05]		0.147	0.234	[2.76]	***
Q5-Q1	0.230	31%	0.495	-0.202	[-2.03]	**	0.192	0.069	[0.75]	
Panel B: Buy-and-Hold										
BBW Factor Model										
Q1	0.208	2%	0.018	0.226	[3.30]	***	0.009	0.219	[3.20]	***
Q5	0.332	4%	0.090	0.255	[3.60]	***	0.033	0.307	[4.36]	***
Q5-Q1	0.124	7%	0.108	0.029	[0.46]		0.043	0.088	[1.44]	
Augmented BBW Factor Model										
Q1	0.141	2%	0.018	0.157	[2.89]	***	0.009	0.150	[2.77]	***
Q5	0.298	4%	0.090	0.221	[3.36]	***	0.033	0.273	[4.25]	***
Q5-Q1	0.157	7%	0.108	0.064	[1.04]		0.043	0.123	[2.06]	**

Internet Appendix A: Variable Definitions

The table shows the definitions of the main variables used in the paper.

Variable	Definition	Source
Bond Variables		
Bond Book/Market	Bond's book value divided by its market price. (Book value, an amortizing issue price, linearly converges to the bond's face value at maturity)	TRACE, Mergent FISD
Bond Mispricing	-1 * Residual/ Market Value of Total Liabilities of firm	
Bond Yield	Yield to maturity (%)	TRACE, Mergent FISD
Bond Credit Spread	Difference between yield of bond and swap rates with matched cash flows	TRACE, Bloomberg
Bond Value	Market value of bond	TRACE, Mergent FISD
Bond Face Value	Face value of bond	Mergent FISD
Bond Age	Years elapsed since issuance	Mergent FISD
Bond Maturity	Remaining time to maturity (in years)	Mergent FISD
Bond Duration	Macaulay duration of bond (in years)	TRACE, Mergent FISD
Bond Coupon Rate	Coupon rate of bond (%)	Mergent FISD
Bond Bid/Ask Spread (Institutions)	Bid/Ask spread of bond. Daily spreads are computed as the difference between average dealer sells and average dealer buys, scaled by the average of buys and sells in the day. We use dealer-to-customer trades only. Monthly spread is the average of daily spreads in month t. Bond Bid/Ask Spread Institutions only uses transactions with volume no less than 100,000 dollars.	TRACE
Bond Reversal	Returns of bond in month t	TRACE, Mergent FISD
Bond Momentum	Six-month returns over month $t-6$ to $t-1$, computed using the beginning of the month price in $t-6$ and the end of the month price in $t-1$.	TRACE, Mergent FISD
Bond Rating	Rating of bond expressed in numerical values from AAA (1) to D (22). Credit rating is from S&P when available, and from Moody's when S&P's rating is not available.	Mergent FISD
Bond Volume (Institutions)	Dollar transaction volume for a bond in a month. Bond Volume Institutions only uses transactions with volume no less than 100,000 dollars.	TRACE
Number of Trades (Institutions)	Number of all transactions for a bond in a month. Number of Trades Institutions only uses transactions with volume no less than 100,000 dollars.	TRACE
Number of Bonds t+1	Number of outstanding bonds of firm in month $t+1$	Mergent FISD
Percent of Bond Market Capitalization Traded in t+1	Percentage of the market value of the issuing firm's bonds that trade in month $t+1$ as a fraction of the market value of the firm's bonds with signals in month t	Mergent FISD
Number of Days from Beginning of Month t+1	Difference in calendar days between the date of first transaction in month $t+1$ and the first trading date of month $t+1$.	TRACE
Number of Days from End of Month t+1	Difference in calendar days (in absolute values) between the last trading date of month $t+1$ and the date for month $t+1$ end-of-month transaction.	TRACE
Investment Grade	Dummy variable which equals one if bond's credit rating is BBB- or above.	Mergent FISD
Non-Investment Grade	Dummy variable which equals one if bond's credit rating is BB+ or below.	Mergent FISD
Offering Price	Price at which bond is initially sold to investors.	Mergent FISD
Bond Market Factors		
Bond Market Factor	Excess return on the value-weighted corporate bond market portfolio.	TRACE, Mergent FISD
Bond Value at Risk Factor	Return difference between bonds with low value-at-risk (as measured by the second worst return in the previous three years) and bonds with high value-at risk. Bonds are independently sorted into 25 value-weighted portfolios based on credit rating and value-at-risk, and the factor is formed as the average across rating quintiles.	TRACE, Mergent FISD
Bond Rating Factor	Return difference between bonds with high default risk (as measured by credit rating) and bonds with low default risk. For each of the double-sorts on value-at-risk, illiquidity and reversal, a rating factor is formed by taking the average across the non-rating characteristics. The rating factor is the average of the three factors.	TRACE, Mergent FISD
Bond Illiquidity Factor	Return difference between bonds with high illiquidity (the Roll measure) and bonds with low illiquidity. Bonds are independently sorted into 25 value-weighted portfolios based on credit rating and illiquidity, and the factor is formed as the average across rating quintiles.	TRACE, Mergent FISD
Bond Reversal Factor	Return difference between bonds with low reversal (the past one-month bond return) and bonds with high reversal. Bonds are independently sorted into 25 value-weighted portfolios based on credit rating and reversal, and the factor is formed as the average across rating quintiles.	TRACE, Mergent FISD
Bond Term Structure Factor	Return difference between bonds with long time-to-maturity and bonds with short time-to-maturity. Bonds are independently sorted into 125 value-weighted portfolios based on credit rating, coupon rate and maturity, and the factor is formed as the average across rating and coupon rate quintiles.	TRACE, Mergent FISD

(continued)

Internet Appendix A: Variable Definitions (continued)

Variable	Definition	Source
Equity/Firm Variables		
Equity Mispricing	-1 * Residual/ Market Capitalization (Bartram and Grinblatt 2018, 2020)	
Beta	Annual Market Beta	CRSP
Market Capitalization	Stock Market Capitalization of Common Stock, calculated as product of Share Price (PRC) * Number of Shares Outstanding (SHROUT)	CRSP
Book/Market	(Book Equity (CEQQH) + Deferred Taxes Balance Sheet (TXKITCQH))/Market Capitalization	CRSP, Compustat
Short-term Reversal	Return in prior month	CRSP
Momentum	Return in prior year excluding prior month	CRSP
Long-term Reversal	Return in prior five years excluding prior year	CRSP
Accruals	Accruals = [NOA(t)-NOA(t-1)]/NOA(t-1), where NOA(t) = Operating Assets (t) - Operating Liabilities (t). Operating Assets is calculated as total assets (ATQH) less cash and short-term investments (CHEQH). Operating liabilities is calculated as total assets (ATQH) less total debt (DLCQH and DLTTQH) less book value of total common and preferred equity (CEQQH and PSTKQH) less minority interest (MIBTQH) (Richardson et al., 2001, p. 22)	Compustat
SUE	Quarterly earnings surprise based on a rolling seasonal random walk model (Livnat and Mendenhall, 2006, page 185)	Compustat
Gross Profitability	(Revenue (SALEQH) - Cost of Goods Sold (COGSQH))/Total Assets (ATQH) (Novy-Marx 2013)	Compustat
Earnings Yield	Earnings/Price (Penman, Richardson, Riggoni, and Tuna, 2014)	Compustat
Nearness to Default	Negative of distance to default of firm over the one-year horizon (Schaefer and Strebulaev, 2008)	CRSP, Compustat
Market Value of Total Liabilities	Total Liabilities (LTQH) - Face Value of Bonds + Market Value of Bonds	Compustat, TRACE
Firm-level Fundamentals for BG Signal		
ATQH	Assets - Total - Quarterly	Compustat
DVPQH	Dividends - Preferred/Preference - Quarterly	Compustat
SALEQH	Sales/Turnover (Net) - Quarterly	Compustat
SEQQH	Stockholders Equity - Total - Quarterly	Compustat
IBQH	Income Before Extraordinary Items - Quarterly	Compustat
NIQH	Net Income (Loss) - Quarterly	Compustat
XIDOQH	Extraordinary Items and Discontinued Operations - Quarterly	Compustat
IBADJQH	Income Before Extraordinary Items - Adjusted for Common Stock Equivalents - Quarterl	Compustat
IBCOMQH	Income Before Extraordinary Items - Available for Common - Quarterly	Compustat
ICAPTQH	Invested Capital - Total - Quarterly	Compustat
TEQQH	Stockholders Equity - Total - Quarterly	Compustat
PSTKRQH	Preferred/Preference Stock - Redeemable - Quarterly	Compustat
PPENTQH	Property Plant and Equipment - Total (Net) - Quarterly	Compustat
CEQQH	Common/Ordinary Equity - Total - Quarterly	Compustat
PSTKQH	Preferred/Preference Stock (Capital) - Total - Quarterly	Compustat
DLTTQH	Long-Term Debt - Total - Quarterly	Compustat
PIQH	Pretax Income - Quarterly	Compustat
TXTQH	Income Taxes - Total - Quarterly	Compustat
NOPIQH	Nonoperating Income (Expense) - Quarterly	Compustat
AOQH	Assets - Other - Total - Quarterly	Compustat
LTQH	Liabilities - Total - Quarterly	Compustat
DOQH	Discontinued Operations - Quarterly	Compustat
LOQH	Liabilities - Other - Total - Quarterly	Compustat
CHEQH	Cash and Short-Term Investments - Quarterly	Compustat
ACOQH	Current Assets - Other - Total - Quarterly	Compustat
DVQH	Cash Dividends (Cash Flow) - Quarterly	Compustat
LCOQH	Current Liabilities - Other - Total - Quarterly	Compustat
APQH	Accounts Payable - Quarterly	Compustat

(continued)

Internet Appendix A: Variable Definitions (continued)

Variable	Definition	Source
Bond Market Factors (21-Factor Model)		
Default Spread	Monthly Default Return Spread (DEF) (difference between long-term corporate bond and long-term government bond returns)	Amit Goyal website
Term Spread	Monthly Term Spread (TERM) (difference between the long-term government bond return and the one-month Treasury bill rate)	Amit Goyal website
Fixed Income Value Factor	The value factor on government bonds proposed by Asness, Moskowitz and Pedersen (2013), where value is measured using 5-year changes in 10-year yields.	AQR/Toby Moskowitz website
Fixed Income Momentum Factor	The momentum factor on government bonds proposed by Asness, Moskowitz and Pedersen (2013).	AQR/Toby Moskowitz website
Excess Return U.S. Treasury Bonds Intermediate Maturity	Excess return on the subindex of the U.S. Treasury Index, focusing on securities with less than ten years to maturity, excluding Treasury bills.	DataStream
Excess Return U.S. Treasury Bonds Long Maturity	Excess return on the subindex of the U.S. Treasury Index, focusing on securities with ten years or more to maturity.	DataStream
Excess Return U.S. Corporate Bonds Investment Grade	Excess return on the index for investment grade, fixed-rate, taxable corporate bonds, including U.S. dollar-denominated securities publicly issued by U.S. and non-U.S. industrial, utility and financial issuers.	DataStream
Excess Return U.S. Corporate Bonds High Yield	Excess return on the index for U.S. dollar-denominated, high-yield, fixed-rate corporate securities. Securities are classified as high-yield if the middle rating of Moody's, Fitch and S&P is Ba1/BB+/BB+ or below. The middle rating is the credit rating assigned by Bloomberg when there is disagreement among rating agencies. When three rating agencies provide a rating, then the middle rating is the one provided by two of them. If two agencies provide a rating, then the middle rating is the lower rating of the two.	DataStream
Equity Market Factors (21-Factor Model)		
Excess Return on Market Portfolio	Monthly market index return net of risk-free rate (Mkt_RF)	Ken French website
SMB	Monthly Small Minus Big (SMB) portfolio return (size factor)	Ken French website
HML	Monthly High Minus Low (HML) portfolio return (value factor)	Ken French website
CMA	Monthly Conservative Minus Aggressive (CMA) portfolio return (investment factor)	Ken French website
RMW	Monthly Robus Minus Weak (RMW) portfolio return (profitability factor)	Ken French website
Momentum	Monthly Momentum (Mom) portfolio return	Ken French website
Short-term Reversal	Monthly Short-term Reversal (ST_Rev) portfolio return	Ken French website
Long-term Reversal	Monthly Long-term Reversal (LT_Rev) portfolio return	Ken French website
Excess Stock Return Bond Book/Market Quintile 1	Monthly excess return on stocks of bonds in bond book/market quintile 1	
Excess Stock Return Bond Book/Market Quintile 2	Monthly excess return on stocks of bonds in bond book/market quintile 2	
Excess Stock Return Bond Book/Market Quintile 3	Monthly excess return on stocks of bonds in bond book/market quintile 3	
Excess Stock Return Bond Book/Market Quintile 4	Monthly excess return on stocks of bonds in bond book/market quintile 4	
Excess Stock Return Bond Book/Market Quintile 5	Monthly excess return on stocks of bonds in bond book/market quintile 5	