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Abstract

Corporate bonds' book-to-market ratios predict returns computed from transaction prices. Senior bonds (even investment-grade) with the 20 % highest ratios outperform the 20 % lowest by 3 %–4 % annually after non-parametrically controlling for numerous liquidity, default, microstructure, and priced-risk attributes: yield-to-maturity, bid-ask-spread, duration/maturity, credit spread/rating, past returns, coupon, size, age, industry, and structural model equity hedges. Spreads for all-bond samples are larger. An efficient bond market would not exhibit the observed decay in the ratio's predictive efficacy with implementation delays, small yield-to-maturity spreads, or similar-sized spreads across bonds with differing risk. A methodological innovation avoids liquidity filters and censorship that bias returns.

Keywords: Credit Risk, Corporate Bonds, Book-to-Market, Market Efficiency, Transaction Costs, Point-in-Time

JEL Classification: G11, G12, G14

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1. Introduction

Research spanning three decades features 'book-to-market' as a key driver of the cross-section of equity returns. Because equities lack accurate models of risk premia, assessing whether risk or mispricing explains equity 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 are easier to infer for bonds 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 amortising 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, hardly alters BBM signal efficacy.

Abundant controls and novel tests cast additional doubt on risk mismeasurement as the source of BBM's significant raw and risk-adjusted spreads. For example, no risk story explains 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 version of equity's book-to-market factor, HML, leavess a significant alpha in time series regressions of BBM return spreads on factors.

Tax and liquidity premia do not explain the anomaly either: high BBM bonds tend to be taxed less and traded more than their low BBM counterparts. Also, their round-trip institutional trading costs are about the same (5 bp higher for the highest BBM quintile), while regressions employing interactions between liquidity and BBM show that bonds with high vs. low bid-ask spreads, trading volume, or numbers of trades exhibit similar degrees of BBM return predictability. However, bonds with more negative serial covariances ('gamma') at high return frequencies have greater BBM spreads.

BBM is one when a bond is issued, then rises above or falls below one due to changing economic forces or sentiment. If BBM broadly proxies for omitted controls, 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 risk/liquidity 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 far 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. Plausibly, sentiment's price distortions apply to only a few of BBM's extreme-quintile bonds, requiring distortions to be large to account for BBM's quintile spreads. In this case, BBM likely influences quintile returns only briefly because the vast majority of bonds caught up in the extreme quintiles' wide nets are priced fairly. Such bonds have no reason to share the quintile-exiting convergence to fair value of their grossly mispriced siblings.

Corporate bonds' thin trading has hindered research attempting 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 more 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.

To avoid liquidity filters, we impute monthly returns using the martingale property of fair risk-adjusted asset prices[2]. The 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, is a perfect martingale. In this case, the bond's imputed, unbiased beginning- and end-of-month flat prices generate noisy return estimates that have a small upward bias due to Jensen's inequality.

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[1] Chordia et al. (2017) use a mix of dealer quotes and bonds in TRACE that trade in the last five 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.

Current yields can differ from a bond's expected return. For example, riskless bonds issued at par can become discount bonds, generating higher BBMs when interest rates increase. Yet, riskless discount 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 prices conservatively estimates the true return spread for the full month. A BBM effect in end-of-month trader quotes further supports our claim.

Risk-adjusted profits from the monthly-rebalanced BBM trading strategy do not survive transaction costs. Such costs may deter arbitrageurs from exploiting BBM. Yet, buy-and-hold versions of the strategy survive the transaction costs incurred by larger trades, enhancing overall net performance if such trades avoid additional short sales constraints and costs[3]. Modest tilts of long-only portfolios towards high BBM and away from low BBM bonds can avoid short sales and enhance performance.

Arbitrage can prevent liquid bonds' prices from falling prey to sentiment's distortions. Earlier, we noted that one of our liquidity measures, gamma, alters BBM strategy efficacy. This is not a liquidity premium as enhanced efficacy means illiquid high BBM bonds earn higher returns but illiquid low BBM bonds earn lower returns. Illiquidity serves only as a friction that deters arbitrageurs from correcting the smaller bond price distortions sentiment might cause. But small distortions can grow into larger distortions, becoming attractive targets for correction — particularly when liquidity improves.

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 US 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 the US. Finally, Brooks et al. (2020) show that exposure to traditional risk factors largely explains the active returns of fixed income managers.

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[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) summarise 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. In our sample period, the book-to-market equity anomaly has reversed. Value minus growth quintile spreads (for the equities associated with the bonds in our sample) are –13 bp/month (equal-weighted) and –29 bp/month (value-weighed), while Fama and French's HML earned –24 bp/month, with all three insignificant.

Research on whether corporate bond prices reflect public information and on which corporate bond characteristics account for their returns' cross-section is nascent. In Gebhardt et al. (2005), 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 correlate with past bond returns. Choi and Kim (2018), Israel et al. (2018), Avramov et al. (2019), and Bali et al. (2020) study bond factors and anomalies, while Bretscher et al. (2020) show that estimating firms' capital structures with debt market values resolves corporate finance puzzles. 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 adjust BBM trading profits for risk and liquidity with two approaches. The first uses cross-sectional Fama and MacBeth (1973, 'FM') regressions. These control for the bond attributes listed in the paper's abstract, as well as other premia attributes tied to liquidity and equity returns — like equity beta, equity market capitalisation, 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, two versions of a one-factor 'CAPM' model employing an aggregate bond market index, two versions of a two-factor model which adds equity HML to the CAPM model, and a 21-factor model subsuming Houweling and van Zundert's (2017) and Bektić et al.'s (2019) factors. BBM strategy profits remain significant with factor risk adjustments. Like equity book-to-market, factor-adjusted profits are larger for 'small bonds'.

The adjusted profits are not contaminated by market microstructure biases or off-market pricing — offered to favoured customers or from central dealers. They are also not due to long-term return reversals (Bali et al., 2019). Lastly, for the 20 % of bonds that are closest to default, BBM has about the same efficacy as it does for the sample's complementary bonds. The irrelevance of default risk for BBM efficacy, as well as its similar efficacy for investment-grade and non-investment-grade bonds, casts doubt on omitted risk controls as the source of the BBM anomaly.

BBM does *not* predict US Treasury returns, indicating that controls adequately capture term structure effects. We also show that imputing monthly returns for Treasuries, from their intra-month prices at the transaction dates of our sample's more thinly traded corporate bonds, leads to the same 'non-result'. Robustness tests show that BBM is a better predictor of the risk-adjusted returns of a universe of 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.

2. Data and methodology

Prices for signals and bond returns largely come from TRACE's enhanced (pre-April 2020) and standard 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. We mostly focus on 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 necessary filters, outlined below, 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 also studies all TRACE fixed-coupon bonds, covering 565 093 observations.

Both TRACE samples, i.e. senior unsecured and all bonds, exclude trades reported to occur before the bond is issued or after it matures, as well as trades reported as cancelled, attached to non-U.S. firms, denominated in non-US 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. Like 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 the WRDS Monthly Corporate Bond File. A WRDS return in month $t + 1$ requires a minimum of two trades for the bond — each in the last five days of months t and $t + 1$[6]. Our return requirement is less restrictive, so every WRDS return observation (with identical filters) has a corresponding return in our sample, but the reverse is not true. Robustness tests analyse returns from Merrill Lynch month-end trader marks, with the same start month as TRACE, but ending December 2016, covering 140 808 observations.

We analyse month $t + 1$ profits from trading signals 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 return month's first day. The latter is the earliest transaction date we might use to impute 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.

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[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.

[6] There are several definitions of returns in the WRDS database, but this is the version used in the literature (e.g., Bai, Bali and Wen 2023).

2.1 Return construction

Unlike equities, bonds trade infrequently and often at large bid-ask spreads. To address these issues, we apply the martingale property. This property says that 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 monthly interest earned when transaction dates are close to the month-end price estimation date. For our sample, price-estimating trades are typically about two to three 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 'full price', consisting of the flat price plus interest accrued. 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. the 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 be a martingale. While monthly changes in accrued interest plus distributions do not perfectly match the compensation for the time value of money and risk, they are close approximations, particularly for short periods. Portfolio diversification makes the approximation more innocuous. Finally, any failing of the martingale hypothesis implies our results are conservative, as the paper's introduction explained. These insights validate substitution of flat bond prices from transactions at nearby dates for the month-end flat prices that would be observed 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 imputed 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 trade date used for imputation and the end of the month, as well as the spread charged by the party providing 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 a bond's beginning-of-month flat price, P^B, as the flat price from its first trade that month. Thus, a 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:

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

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 as it likely reflects error in recording the common price used in consecutive returns. Cumulated six-month returns, a momentum control, is computed analogously to equation (1), using a single beginning and single ending price over the six-month horizon. As in equation (1), the six-month return 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 from beginning-price imputation upwardly biases its return estimates—analogous to the upward bias in equity returns (Blume and Stambaugh, 1983). However, our results focus on return spreads between BBM quintiles. If biased returns affect the BBM strategy's long and short legs equally, their return spread eliminates the bias. If the short leg's bias is greater (as implied by trading frequency evidence), our return and alpha spreads underestimate the true spreads. This differs from the conservative spreads generated by martingale violations. Recall, the latter spreads stem from the tendency of discount (high BBM) bonds' flat prices to rise, making intra-month flat price changes understate full-month changes; likewise, premium (low BBM) bonds' flat prices tend to fall, making intra-month changes overstate full-month changes. These two estimation imperfections thus imply wider BBM return and alpha spreads than we report.

Bonds in Default. TRACE reports prices whenever bonds in default trade. We use these 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 be martingales—motivating adjustment of their beginning- and end-of-month $t + 1$ price estimates. The adjustment we apply deliberately underestimates defaulted bonds' returns[7]. This makes our return spread estimates conservative be-

[7] 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 denominator.

cause we understate the returns of long positions in defaulted bonds and there are no defaulted bonds in our strategies' short positions. This conservatism is 'overkill'. Bonds commencing default in month $t + 1$ are rare, even for the strategies' long positions. Defaulted bonds represent only 0.04 % of BBM's long position investment.

Original Issue Discount Bonds. The flat prices of original issue discount bonds tend to appreciate and thus cannot be martingales. However, sizable discounts are rare: 99.8 % of issue prices are above USD 90, fewer than 0.1 % are below USD 50, and the average issue prices of the five BBM quintile portfolios are all close to USD 99.5. Moreover, the numbers of days of amortisation 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.

2.2 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 USD 120 million customer bond sale to one or more dealers, executed as three USD 40 million sales on three consecutive days: 29 and 30 April and 1 May. 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 30 April's (e.g. WRDS computation of the bond's return) or 1 May's transaction provides the return's beginning price. Trade splitting at the ask or favourable pricing by dealers to trades straddling a month's end induce similar correlation. Scenarios that artificially induce 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 USD 100 face amount is a bond's amortised issue price. Table 1, Panel A reports issue price distributions, sourced from Mergent (Fixed Income Securities Database, FISD). For most bonds, the FISD issue price is near USD 100. (With USD 100 assumed as the book value of all bonds, BBM's ability to predict returns is highly significant, but slightly reduced.) If the bond is issued at a discount or premium, we apply the accounting rule that linearly amortises the premium or discount to maturity on month-end dates to arrive at the bond's (end-of) month t book value. For the 30 % of cases where FISD lacks the issue price, we omit the bond as a potential trade.

Month t's BBM signal is Book/P^S. The signal's flat price per USD 100 of face amount, P^S, is taken from the bond's most recent transaction (excluding month t's last seven days). Even when signal prices are from stale trades, the information represents what is available at the end of month t, thus directing 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 month t + 1's bond return estimate. For the senior unsecured bonds that researchers traditionally study ('traditional bonds') and that we focus on in all but Table 8, 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 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.

2.3 Alpha tests for signal efficacy and control variables

We sort bonds into quintiles at month t's end. Quintile 5 has the most value oriented (highest BBM) bonds. We primarily analyse 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. Here, the monthly regression's unit of analysis is the bond. We cross-sectionally regress month t + 1's bond returns (computed with Section I.A's procedures) on BBM quintile dummies or normal scores and quintile dummies for numerous controls. The coefficients on each regressor are then averaged across months. The controls consist of bond attributes and issuing firms' equity characteristics measured (in contrast to the signal's eight-day gap) as close to the end of month t as possible. These controls include each bond's yield-to-maturity ('YTM')[8], credit spread, credit rating, value outstanding, time to maturity, duration, age, past seven-month return excluding the prior month ('bond momentum'), past one-month return ('bond reversal'), bid-ask spread, and nearness to default. Equity characteristics include equity market beta, equity market capitalisation, equity book-to-market, past one-month stock return ('short-term reversal'), past five-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. These controls, detailed in Internet Appendix A, are rooted in past literature and textbooks[9]. Many controls are

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[8] BBM tends to rise and fall with YTM. Neither BBM nor YTM directly map into an expected return. However, YTM, deployed as a function of dummy variables for YTM ranks, better captures expected returns than the cruder BBM.

[9] Robustness tests explore parametric controls. In addition to papers cited earlier, Grinblatt and Titman (2002, Chs. 2, 23) discuss yield-to-maturity, 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) analyse nearness to default. Bartram and Grinblatt'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.

highly correlated, complicating inferences from their coefficients. Most FM regressions also include market microstructure/liquidity controls measured in the return month, $t + 1$, as well as industry dummies.

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; 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. A robustness check with a necessarily shortened sample period and smaller cross-section includes the bond's past three-year return, skipping a year.

Because Equation (1)'s 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 stylised 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. 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 past research has shown that they explain these poorly[10]. Such models also have implications for returns, showing 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 one-month LIBOR) of BBM quintile portfolios on factor portfolio returns is an alternative to FM regressions for risk

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[10] Eom et al. (2004) fit the credit spreads of 182 bonds to structural models, finding poor matches with observed credit spreads. Huang and Huang (2012) conclude these models are deficient at pricing bonds, even at the ratings level. Huang et al. (2020) document failures to fit CDS data. Collin-Dufresne et al. (2001)'s bond-level regressions of credit spreads on stock returns and other control variables show structural models' poor fits.

adjustment. Regression intercepts or spreads between 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, value-at-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 value-at-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 six-factor model that adds a term structure factor to BBW's five factors, two versions of a one-factor CAPM model with a bond index as a factor, two versions of a two-factor model, which adds equity HML to the CAPM factor, and a customised 21-factor model.

2.4 Summary statistics for the overall sample

Table 2, Panel A lists summary statistics for BBM and other attributes of the senior unsecured bonds and their issuing firms. Each row shows time series averages 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 % 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.

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]. Not surprisingly, such bonds have higher bond betas, volatility, and value-at-risk (a downside risk measure). They also have higher YTMs, lower market value, higher bid-ask spreads, greater trading volume, larger numbers of trades, and been issued more recently and by firms with more bonds, higher equity betas, poorer past year equity returns, 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), and the least negative serial covariance (bond gamma)[13], and come from larger firms

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[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.

[13] Bond gamma, based on Roll (1984), was used in BBW and Bao et al. (2011) to represent temporary price movements and hence illiquidity. Table 2 shows that gamma shares a similar correlation with BBM as our direct measure of a bond's effective bid-ask spread. Using gamma as a control in place of our direct measure of bid-ask spreads

with the highest stock returns over the past year (equity momentum)[14]. 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), shifts in the risk-free term structure impose greatest risk on the 20 % lowest BBM bonds.

The flat prices of BBM Q5 bonds, which typically trade at discounts, tend to appreciate, while Q1 bonds depreciate. Thus, Q5 bond purchasers tend to earn capital gains, while Q1 purchasers earn capital losses, even if both bond types earn identical returns. (The other return component, current yield, likely offsets expected shrinkage of flat price discounts and premiums.) When realised, the gains and losses will generally be taxed at lower rates and in the more distant future than accrued interest or amortisation. Thus, tax considerations argue for negative Q5–Q1 risk-adjusted return spreads. We now analyse raw return spreads before turning to adjustments for risk or illiquidity.

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 rows 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 % annualised 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 spread's t-statistics correspond to annualized Sharpe ratios of 0.92 (EW) and 0.85 (VW). Both exceed the 0.40 Sharpe ratio for equity HML (over a longer sample period) reported by Ehsani and Linnainmaa (2022). Table 2, Panel B's last two rows stratify the top row (EW) by bond size. Small bonds have larger returns within each quintile and a larger BBM effect than large bonds. (The two sequentially sorted rows do not average to the top row because some bonds lack face value outstanding data.) 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

has little effect on our findings, as Appendix B notes. However, its interaction effects with BBM are stronger, as the paper later documents.

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

t + 2's first trade or later) are –0.001 for EW Q5 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 increase BBM's reported extreme quintile spread by about 8 bp.

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 inflate Panel B's spreads, albeit negligibly, if the unobserved full-month spreads of no-trade bonds are small or spreads in one-trade bonds' flat price changes are negative. 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. To address martingale violations, 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* spread in 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 ending price bid-ask pairs for month *t* + 1's returns. It lists 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 their reliance on bid and ask prices for inputs.

3. Bond book-to-market and the cross-section of expected bond returns

Many return-influencing attributes correlate with BBM. We therefore analyse 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.

3.1 Fama-MacBeth cross-sectional tregressions

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. Table 3 Panel A's four odd-numbered specifications regress bond returns on BBM and controls, each expressed as dummy variables corresponding to Q2 through Q5, with Q1 omitted for the intercept. For brevity, Table 3, Panel A only reports the coefficients for the Q5 dummy variables, which is Q5–Q1's return spread 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 (non-categorical) 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.

Specification 1 shows that BBM Q5 bonds outperform Q1 bonds by 44 bp per month ($t = 3.62$), controlling for industry fixed effects. The 0.14 coefficient on the parametric BBM signal is also significant ($t = 3.13$) as Specification 2 shows. Specifications 3 and 4 illustrate that microstructure controls barely affect results: BBM's average coefficient is similar, whether comparing Specification 3 with 1, or 4 with 2. Omitted for brevity, the relatively small effect of market microstructure also applies to the remaining two specifications. Thus, identifying returns with the martingale procedure does not distort inferences. Adding bond-specific controls (Specifications 5 and 6) reduces BBM's influence on a bond's month $t + 1$ return by about 40 %, but the BBM effect remains highly significant. Specification 7 and 8's controls related to equity returns increase BBM Q5's coefficients compared to Specifications 5 and 6 by about 20 % and increase significance as well. Moreover, Specifications 7 and 8 establish that equity book-to-market does not predict bond returns once BBM is controlled for.

Outliers. Results are also not driven by outliers. Eliminating observations that rely on the top 100 or bottom 100 bond prices negligibly alters our findings.

Callable Bonds. BBM Q5 does not outperform Q1 because bonds tend to be called when their fair value (in the absence of a call) exceeds the call price. Filtering out bond returns in months approaching call dates or adding controls for call dates has little effect on BBM's alpha spread.

Parametric Controls. Our use of quintile dummy control variables in Table 3, Panel A to better proxy for a nonlinear relationship does not explain our findings. Table 3, Panel B's Column 1 parrots Panel A, Specification 7's use of all FM controls but shows similar results with parametric versions of the control variables. This leftmost column reports a BBM quintile spread of 29 bp (t = 4.52).

Prices from month-end trader marks. 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 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) when value weighted. The associated alpha spread (Panel B, Column 2) is 20 bp per month (t = 2.52). Using Merrill's marks for the prices of the BBM signal as well (Column 3) generates a larger, more significant alpha spread of 50 bp per month (t = 5.03) but has bias from error in the price mark shared by both BBM 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. Table 3, Panel B's rightmost column studies the exclusively investment-grade (IG) subsample of traditional bonds. After sorting IG bonds into BBM quintiles, the rightmost column reports Specification 7 of Table 3, Panel A. The IG subsample's BBM Q5 coefficient, 0.307 (t = 5.97), is similar to Table 3 Panel A's coefficient, but more significant. With BBM dummies from an independent sort of IG and BBM, the (unreported) BBM Q5 coefficient is 0.321 (t = 5.01).

Long-Term Bond 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 three-year past return, measured from months t – 48 to t – 13, predicts return reversal. We omitted this past return control because its lengthy horizon halves the average number of bonds each month and cuts 42 months from the sample. Yet, in horse races between the three-year past return and BBM, using Table 3 Panel A's key specifications (plus the thre-year past return), the three-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, BBM Q5's coefficients are 0.250 (t = 2.55) and 0.303 (t = 3.29), while the three-year past return Q5 coefficients are 0.006 (t = 0.08) and –0.016 (t = –0.20), respectively. Thus, as a corporate bond return predictor, BBM subsumes the prediction power of the three-year past return.

Further robustness tests. Additional robustness tests for Table 3 are discussed in Internet Appendix B. It shows that adding controls for bond (one-factor) beta, volatility, and value-at-risk have little impact on our findings (Internet Appendix Table IA.1). Similarly, replacing Table 3's bid-ask spread control with gamma illiquidity still leaves a significant BBM anomaly, but one that (with a comparable sample) is virtually identical in magnitude and significance to Table 3 (Internet Appendix Table IA.2). Finally, it shows that the BBM signal is distinct and separate in its effects from a mispricing signal developed by Bartram and Grinblatt (2018, 2021) (Internet Appendix Table IA.3).

3.2 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 one-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 α_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 five-factor model controls for overall bond market, credit, value-at-risk, liquidity, and short-term bond return reversal factors; the augmented BBW six-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. The VW spread, 12 bp per month, is smaller than the EW spread and statistically insignificant. The small EW and VW alpha spreads in Table 4, Panel A may stem from the five-factors' lack of a term structure control; bonds with similar maturity tend to covary more with each other than with different maturity bonds. To control for term structure risk, Table 4, Panel B supplements BBW's factors with a term structure factor created in the spirit of BBW. We independently triple sort 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.

Return biases due to bid and ask distributions, as well as Jensen's inequality, prevent assessment of whether Table 4's observed spreads stem 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. BBM's effects may also differ across risk adjustment methodologies because Table 4 lacks factors for many other controls in Table 3, Panel A's FM regression, like bond size. Table 4, Panel C's top four rows illustrate the effect of bond size on factor model EW alpha with the BBW five-factor and augmented six-factor models[15]. With both models, bonds with less than intra-quintile median market capitalisation have larger and more significant alpha spreads than bonds with larger value outstanding. With the five-factor model, EW portfolios of 'large bonds' exhibit no significant alpha spread. With the augmented six-factor model (third and fourth rows), the small-bond alpha spread is a significant 28 bp, and lies between the 27 and 32 bp alpha spreads from Specifications 5 and 7 in Table 3, Panel A. 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 five-factor model, suggests that large bonds may be more efficiently priced than small bonds. BBM's greater efficacy at predicting small-bond risk-adjusted returns mirrors equity's parallel finding.

[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.

Alternative Factor Models. As an alternative to the BBW factor models, Panel C also reports alphas and alpha spreads from two versions of one-factor ('CAPM') and two-factor ('CAPM + HML') models. The one-factor models' spreads are intercepts from regressing returns on a value weighted index of either the WRDS returns of all WRDS bonds or of the martingale-based intra-month returns of all bonds used in our sample of traditional bonds; two-factor models add equity HML as the second factor. The alternative factor models show significant and similar alpha spreads (about 30 bp per month).

Robustness. Further robustness tests of the raw returns and factor model alpha spreads are found in Internet Appendix B. These tests find that there are significant alpha spreads with a 21-factor model described in Appendix B (Table IA.4), that BBM's CAPM alphas are larger for investment grade bonds (Table IA.5), and that neither volatility, individual bond market betas, value at risk, nor bond institutional ownership materially influence BBM spread magnitude (Table IA.6).

4. Understanding the BBM alpha spread: risk or mispricing?

4.1 Signal delay

Figure 2 plots alpha spreads (BBM's Q5 dummy coefficients from Specification 7, Table 3, Panel A) for signal delays ranging from 0 to 11 months. Unlike Table 3, Figure 2's returns always commence in 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, approximates the 32 bp coefficient from Table 3, Panel A despite a shorter return series. Figure 2 indicates an alpha spread decline to 9 bp when signal delay is two months, losing about 70 % of its efficacy. The spread meanders with further delay, ranging from 2 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]. BBM's slow evolution implies that if BBM *broadly* proxies for omitted attributes, stale BBM signals should predict bond returns, which is inconsistent with Figure 2.

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[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 two-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.

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 a 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 extreme quintiles generally move to adjacent quintiles. Adjacent quintiles have tighter alpha spreads with their more extreme neighbours 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 alpha decay pattern and extreme-quintile spread size also rule out BBM as a *narrow* proxy for the omitted risk/liquidity attributes of a small proportion of these quintiles' bonds. As a narrow proxy, the omitted risk or liquidity attributes must earn implausibly large premia to account for the extreme quintiles' observed alpha spread, and then have the premia shrink once the bonds 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 attribute earns just one-sixth of the needed spread if it earns a 5 % 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 turn 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 of months for such highly mispriced bonds. Finance teaches that savvy traders should 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 BBM's extreme quintiles explain Table 3, Panel A's results even when the remaining bonds are priced at fair value. When savvy market participants force the prices of highly mispriced bonds to converge to fair value, the formerly mispriced bonds tend to depart their quintiles. Whether they depart or stay, other bonds remaining in the extreme BBM quintile will largely consist of bonds that are close to fair valuations, 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).

4.2 Signal efficacy as a function of default risk and liquidity

Table 3, Panel A's extensive controls for credit ratings, default, and liquidity make it unlikely that omitted 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 Table 2, Panel A's 32 bp (all control) alpha spread is more than twice YTM's spread.

If BBM proxied for inadequate credit risk or liquidity controls, the BBM anomaly may be stronger for bonds that are nearer to default or less liquid. Table 5 adds interactions to Table 3, Panel A's regressors, multiplying each BBM quintile dummy or normal score by a dummy for the 20 % of bonds that are nearest to default (Panel A's top half) or 20 % lowest credit rating (Panel A's bottom half). Panel B correspondingly multiplies each BBM quintile dummy by dummies for either the 20 % of bonds with lowest trading volume, 20 % lowest number of trades, 20 % largest bid-ask spread, or 20 % largest bond gamma (Panel B, appearing top to bottom, respectively). For brevity, reported BBM quintile interactions are only with BBM Q5, representing BBM's Q5–Q1 alpha spread. A positive coefficient here indicates larger BBM spreads for the top 20 % of bonds based on default or illiquidity compared to BBM spreads for the bottom 20 % of default or illiquidity.

All of Table 5 Panel A's specifications have significant BBM Q5 coefficients, implying the BBM anomaly remains for the 80 % of bonds least likely to default. However, the interaction dummies are insignificant. For example, in Specification 7's top half, bonds in the quintile nearer to default have a 10 bp per month *lower* alpha spread than bonds further from default. In all specifications, the 20 % most likely to default bonds and the 80 % least likely have statistically indistinguishable BBM effects.

Table 5, Panel B shows similar findings for the first three illiquidity measures. Here, all but two of BBM's 24 interaction terms with the 20 % least liquid bonds are insignificant. The exceptions are Specification 2 and 4's marginally significant volume interaction, for which the least liquid bonds exhibit stronger BBM normal score predictability, but only with limited regressor controls. With bond gamma as the liquidity proxy (bottom quarter of Panel B), low liquidity bonds earn significantly greater BBM alpha spreads than high liquidity bonds. The significant interaction here is consistent with illiquidity increasing the returns of some bonds and decreasing the returns of others, depending on the BBM quintile. This is not a liquidity premium per se, which raises the returns of similarly illiquid BMM Q1 and Q5 bonds by similar amounts. We would detect such a premium from a significant coefficient on the standalone gamma regressor, but gamma is insignificant in all regressions with bond controls.

Note that each of Panel B's 32 regressions demonstrates that all bonds, irrespective of liquidity quintile, exhibit significant BBM effects, even when liquidity and its interactions are controlled for. Hence, while some forms of illiquidity may enhance the BBM effect, for reasons we will explore later, the enhancement is not because BBM proxies for an omitted or poorly measured liquidity control. Next, we study whether omitted controls tied to the riskless term structure might explain our findings.

4.3 BBM and lower risk treasury notes and bonds

If BBM's anomaly stems from BBM better capturing duration or related interest rate risk measures than our controls, Treasuries should exhibit a BBM anomaly. Using CRSP's US 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 US Treasuries 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 US 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. Here, we force trades in Treasuries to mimic the distribution of trading frequencies in the corporate bond market. At the end of each month *t*, Treasury security *j* is randomly assigned a 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 t +1 return using the latter security's end-of-day prices from days d_1, d_2, and d_3, respectively. 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 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 Panel C. For example, with Specification 5, Panel D's coefficient on BBM Q5 is an insignificant 0.039, whereas Panel C's 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.

4.4 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 its book-to-market ratio. Here, we construct a bond version of HML and show 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 groups (large and small), we compute each month's return spread between a value weighting (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 primary factor regressions, adding BHML factor returns. Table 7's top half corresponds to Table 4 Panel A (the BBW factor model); its bottom half corresponds to Table 4, Panel B (the augmented BBW factor model). For brevity, Table 7 only reports intercepts and factor betas on BHML. Its rightmost column shows 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 no surprise. 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.

5. Junior bonds, trading frequency, and transaction costs

5.1 BBM's return predictive ability for all bonds

Prior analysis studied only senior unsecured bonds with no options other than simple calls. Table 8 repeats Table 3, 4, and 7's regressions, but for all TRACE bonds, including junior and puttable bonds. Table 8, Panel A, which parrots Table 3's FM regressions for the all-bond sample, reports selected coefficients of interest for brevity. Panel B and C's factor 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 8 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 8, 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.

5.2 Off-market prices

The literature is ambiguous about whether dealers offer key customers different prices than others, or whether central dealers offer bid-ask spreads at discounts or premia when providing liquidity. TRACE prices bias inferences if the BBM signal selects time-clustered off-market prices below or above mid-market prices. 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 and vice versa, better becomes worse, higher is lower, etc.) if off-market prices imply key customers get wider rather than narrower spreads, or central dealers offer narrower rather than wider spreads.

Suppose key customers receive better pricing, and their better prices frequently impute TRACE's beginning price for returns. Then customer-dealer trades would earn higher BBM alpha spreads than dealer-to-dealer return-initiating transactions. Table 9 analyses 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 trade used for the return's beginning price makes the key customer hypothesis 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 eight-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 eight-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 key customer hypothesis comes from gap shortening, which should increase the spread if favored customers concentrate trades in short time intervals. Instead, the spread decreases, albeit negligibly, to 43 bp, if the gap is reduced by 5 trading days. When increasing the 8-day gap, even by 16–20 trading days, extreme quintile monthly return spreads still exceed 40 bp.

The irrelevance of gap lengthening and shortening also refutes 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 favoured customers, the clustering of central dealer trades could inflate Q5 signals and returns, while deflating Q1 signals and returns.

For the key customer and central dealer hypotheses to hold, off-market prices must also persist for no more than 13–15 trading days. If persistence was longer, biases in end-of-month prices (typically 13–15 trading days after the beginning-price transaction) would offset the bias in the beginning-of-month transaction price, negating any return bias. Hence, evidence showing that gap lengthening by up to 16–20 trading days scarcely affects return spreads further refutes off-market price hypotheses.

5.3 Buy-and-hold returns

Many institutional investors rebalance their bond portfolios infrequently, reducing transaction costs. Table 10 reports factor model alphas (computed as in Table 4 Panel A) 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[17]. This suggests that yearly rebalancing approximately halves BBM's risk-adjusted profits.

5.4 Transaction costs

BBM's extreme quintile pre-transaction cost alpha spread assesses market efficiency, but a BBM trading strategy is unprofitable if transaction costs exceed gross profits. Corporate bond market transaction costs are generally high (Chen et al., 2007; Edwards et al., 2007; Bao et al., 2011; Feldhütter, 2012), which might deter exploitation of BBM signals as stand-alone 'arb strategies'. Internet Appendix C details how TRACE is used to estimate trading costs from turnover and effective half spreads per dollar trade for every BBM quintile in each month. Month t two-way turnover is twice the sum of the portfolio weights of the bonds leaving the portfolio in month $t + 1$, thus accounting for both purchases and sales. Equation (4) in Internet Appendix

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[17] To address statistical pitfalls from 12-month returns that roll over each month, we apply the technique of Jegadeesh and Titman (1993). 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.

C computes trading costs from two-way turnover.

While dealers meeting customer liquidity needs execute on the profitable side of the bid-ask midpoint, customers can bilaterally negotiate prices with a dealer. Hence, costs may depend on the type of investor, the type of trade, and the relative market power dealers have over the customer (Bessembinder et al. 2009). Consistent with this, Bao et al. (2011) show that large transactions face lower costs in the bond market. Accordingly, we compute two alternative sets of transaction costs. The first includes all dealer-to-customer transactions in TRACE-sourced bonds; the second is limited to dealer-customer transactions with volumes of at least USD 100 000. The latter captures trades that incur tighter bid-ask spreads due to larger customers' greater bargaining power with dealers.

Figure 3 graphs monthly bid-ask spreads for all trades (Panel A) and for large trades (Panel B). It displays the average bid-ask spreads for an equal weighting of all BBM quintiles as well as for bonds in Q1 and Q5. The overall bid-ask spread patterns are consistent with Choi and Huh's (2019) findings. Figure 3 also shows bid-ask spreads spiking during the 2008–2009 financial crisis.

Table 11 reports average portfolio turnover and transaction costs as well as gross and net performance for trades within BBM's extreme quintiles. Net performance is the intercept from regressing quintile portfolio excess returns net of transaction costs on factors. Subtracting transaction costs monthly alters factor betas, so Table 11's net performance is not exactly equal to the difference between Table 4 and Table 10'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 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, which exceeds the alpha spreads computed for the strategy. Even applying the (more than 50 %) lower transaction costs of 19 bp for large trades 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 reduce turnover, as borne out in Panel B with turnover of 7 % and monthly transaction costs of 11 bp and 4 bp for all investors and institutions (i.e. a trade size of USD 100 000 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 five-factor net profit for all customer trades remain insignificant, but the augmented BBW model shows significant net profits of 12 bp (t = 2.06). Thus, the buy-and-hold 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.

5.5 Trading costs and arbitrage barriers

Table 5, Panel B showed that the gamma measure of illiquidity, which is linked to trading costs, significantly predicts returns when interacted with BBM. This finding is consistent with trading cost heterogeneity deterring arbitrage for some bonds but not others. Bao et al. (2011) find that gamma illiquidity correlates with yields, but the paper does not study gamma's effect on returns. Moreover, Table 5, Panel B's Fama-MacBeth regressions control for yield-to-maturity in specifications with bond controls.

Independent quintile sorts of gamma and BBM further assess whether arbitrage-deterring trading costs allow large deviations from fair value to emerge. The deviations entice arbitrageurs to exploit the profit opportunity and, in so doing, drive the BBM anomaly. Table 12 reports raw return spreads along with alpha spreads from the one-factor CAPM model. Table 12 shows modest evidence that arbitrage barriers, tied to transaction costs, account for our findings. BBM spreads are fairly monotonic across liquidity quintiles, irrespective of whether the portfolios are equal- or value-weighted. While unreported, the largest spread changes are driven by illiquidity's enhancement of BBM Q5's return. There is little power to assess liquidity's impact on low-BBM bond alphas, as highly illiquid bonds with very low BBM are rare. So, it is possible that BBM Q1's relatively low return for illiquid bonds is statistical noise or stems from other arbitrage deterrents, like short sales frictions.

6. Conclusion

Differences between the corporate bond and equity markets could influence their relative efficiency. Researchers have conjectured that the corporate bond market may be relatively more efficient because sophisticated institutional investors dominate its trading (Chordia et al., 2017). We believe it is less efficient due to its over-the-counter market structure, engendering greater trading costs and less pre-trade price transparency. Such illiquidity disincentivises arbitrageurs from correcting mispricing that has yet to reach attractive levels. Compounding illiquidity is bond removal from the secondary market. Pension funds, insurers, endowments, and mutual funds — tend to hold purchases for long periods.

Rational trades garner profits only when pricing errors shrink. Here, too, bonds differ from stocks. Their finite nature and more transparent cash flows mean that bond uncertainty tends to resolve with time, bringing fair prices into focus. Arbitrageurs, knowing that bond pricing errors will inevitably shrink, rush to seize on opportunities that exceed costs because delay invites others to steal those profit opportunities for themselves. For stocks, time's passage resolves some uncertainty, but new uncertainties about increasingly important distant cash flows emerge because stocks are perpetual.

To aid understanding of market efficiency, this paper studies book-to-market's role in corporate bond pricing. Alpha spreads between BBM's extreme quintile portfolios — 32 bp per month with the most extensive controls — are sizable considering the volatility of corporate bonds compared to stocks. The raw return spread's Sharpe ratio, 0.92, exceeds those of both the S&P

500 and the Fama and French (1993) HML factor. We study bonds because they have better controls for risk and liquidity, and predominantly come from larger firms, making the BBM spread even more impressive.

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 analyse a larger set of TRACE bonds that includes junior bonds, alpha spreads are considerably larger. Finally, our application of 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 these assumptions, as well as tax considerations, argue for higher BBM spreads than we report.

The paper also presents evidence that the BBM strategy's alpha is likely to stem from mispricing, particularly for small-issue bonds. Alternative explanations, like omitted risk, microstructure, or liquidity controls are inconsistent with the pattern of profits from BBM signal delay, calibrations from yield spreads, and BBM signal efficacy for bonds with more default risk, less liquidity, or bonds hedged with own-firm equity. Then, there is the irrelevance of callability, bond beta, rating, value-at-risk, and market microstructure controls, and the inability of BBW factor risk to explain BBM profits, even with an additional HML-like bond factor. The riskless term structure cannot explain the BBM anomaly either: BBM does not predict US Treasury returns — even when artificially forcing Treasury transactions data to mimic the sparseness of corporate bond transactions. Finally, equity book-to-market and bond book-to-market share relatively weak profitability for larger issues. With large issues, volume can offset low profitability per unit of arbitrage, so mispricing never gets very large. Large issues are also cheaper to trade, studied more, and are far less prone to information asymmetry.

It is not 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, average transaction costs, estimated for different trade sizes, are large enough 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-and liquidity-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.

BBM spreads tend to be larger for higher gamma (i.e. lower liquidity) bonds. This is likely due to arbitrageurs devoting their talents to their most profitable opportunities and is not a liquidity premium per se. For bonds with large gamma, convergence needs to wait until hedge funds find the mispricing large enough to offset its costs. For others, convergence to fair value is left to the supply and demand of less sophisticated agents who trade bonds with less haste and different motivations.

Mispricing may explain book-to-market's effects with 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 the related anomalies of other assets, like equity, where controls are harder to come by. Consistent with the equity mispricing explanation is equity HML's missing premium in the last 25 years, as trading frictions declined and the anomaly became a popular investor discussion topic.

BBM ratios are highly negatively correlated with bond prices. While quintile sorts of 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 BBM 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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Figures and Tables

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.

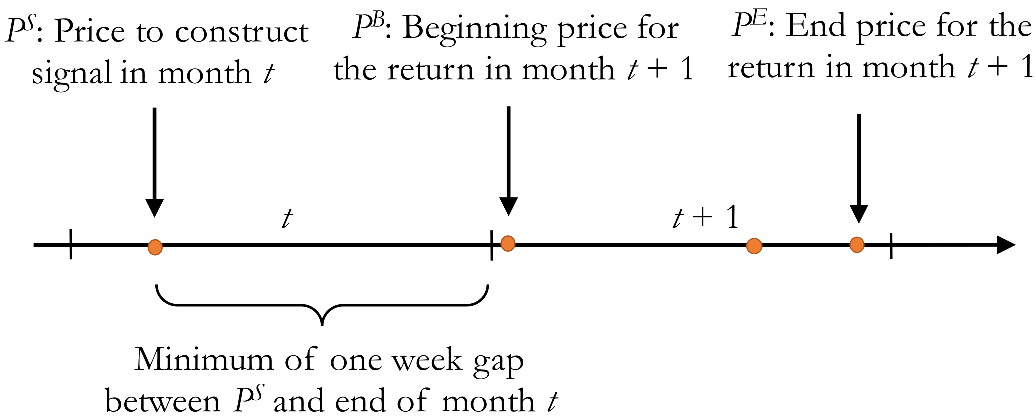


Figure 2. Signal delay

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.

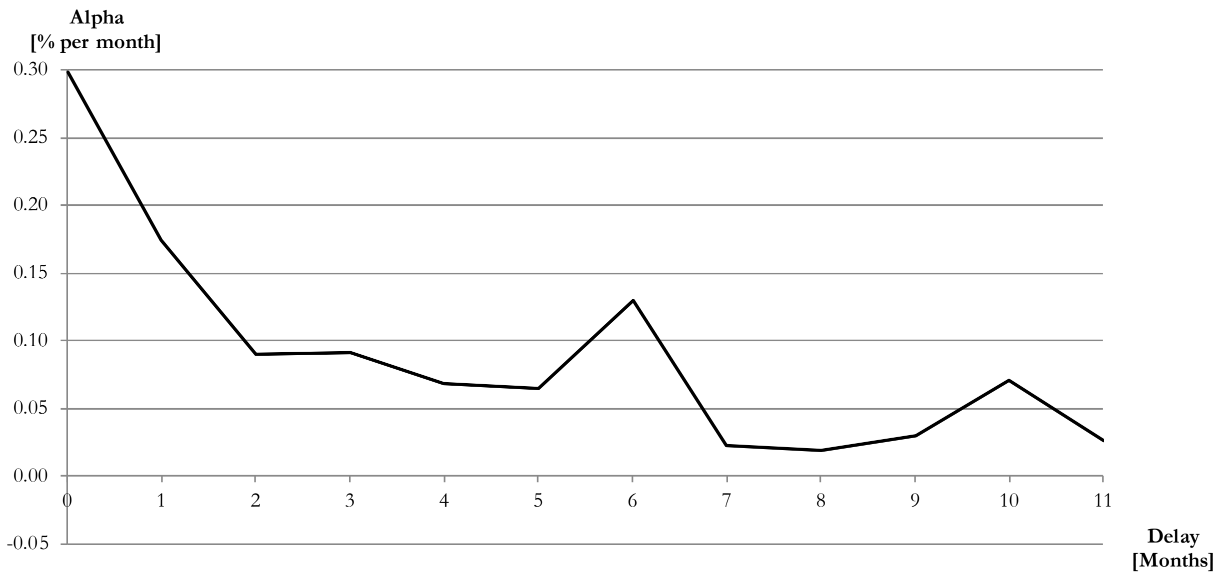
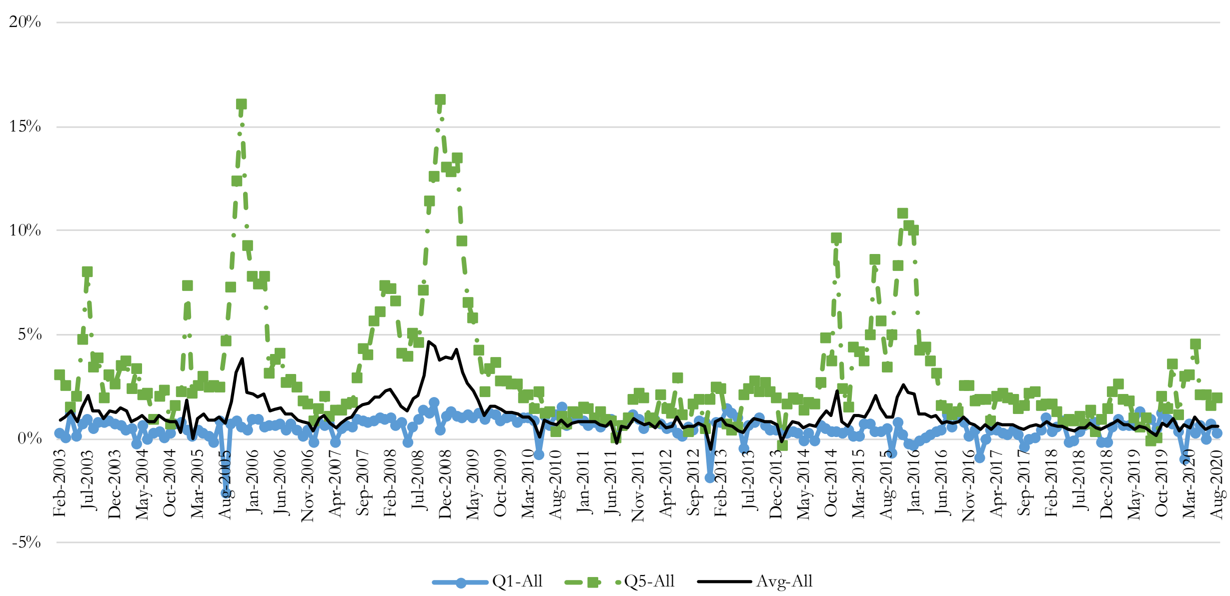


Figure 3. Monthly bid-ask spreads for bond book-to-market quintiles

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

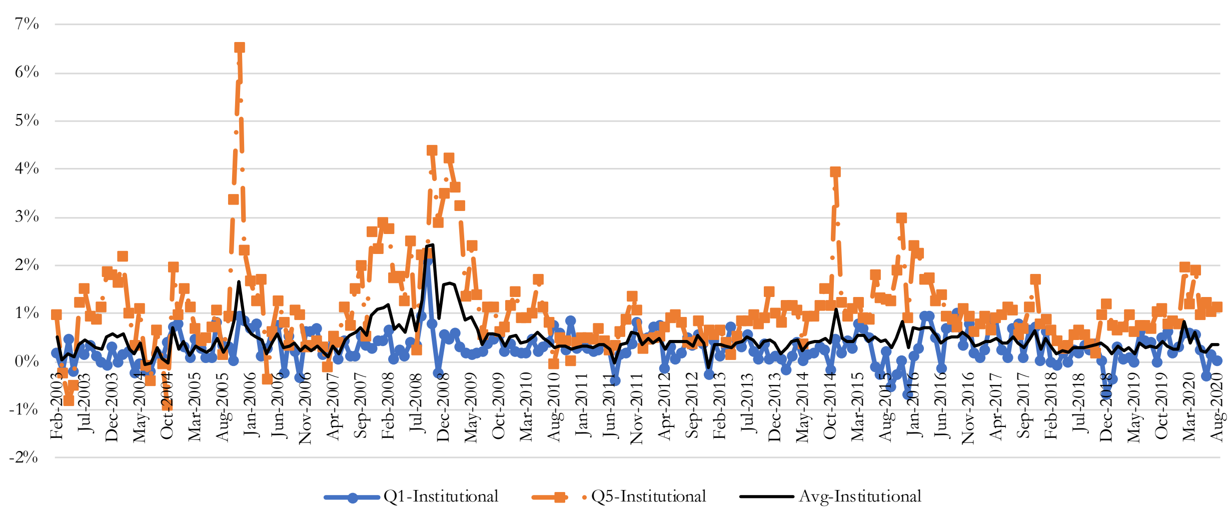


Table 1. Summary statistics

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 USD 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'). The panel also reports the time-series average of the monthly difference between the average characteristics of the fifths and first BBM quintile as well as the associated t-statistic. 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 US dollar-denominated, senior unsecured corporate bonds without embedded options other than call options.

Panel A. Bond and firm characteristics

			Bond Book/Market (BBM) Quintiles					Q5-Q1 (high - low BBM)	
	All	Correlation	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)	Average	t-statistic
Bond Book/Market	0.963	1.00	0.845	0.923	0.961	0.994	1.094	0.250	[35.9]
Bond Mispricing	-0.001	0.29	-0.011	-0.005	-0.001	0.003	0.011	0.022	[34.3]
Bond Coupon Rate	5.513	-0.30	6.818	5.866	5.321	4.744	4.816	-2.002	[-30.5]
Bond Yield	4.779	0.42	4.682	4.218	4.341	4.469	6.191	1.509	[9.9]
Bond Credit Spread	1.579	0.35	1.466	1.300	1.325	1.230	2.571	1.105	[8.3]
Bond Value	532.2	-0.10	610.7	564.3	522.3	508.4	455.2	-155.5	[-14.5]
Bond Face Value	501.7	-0.03	508.0	517.5	500.2	503.2	479.8	-28.20	[-2.5]
Bond Age	4.870	-0.16	7.268	5.083	4.373	3.702	3.926	-3.342	[-16.4]
Bond Maturity	11.18	-0.10	16.41	10.184	8.832	8.445	12.02	-4.385	[-11.0]
Bond Duration	6.984	-0.14	9.388	6.666	5.924	5.688	7.248	-2.140	[-10.2]
Bond Rating	8.159	0.24	7.462	7.901	8.144	8.173	9.126	1.663	[17.2]
Bond Reversal	0.685	-0.05	0.814	0.706	0.665	0.639	0.662	-0.152	[-1.2]
Bond Momentum	3.421	-0.22	4.548	3.752	3.354	2.935	2.871	-1.677	[-3.2]
Bond Volume	49.23	0.10	33.08	40.35	47.66	56.20	68.86	35.78	[13.5]
Bond Volume Institutions	47.93	0.09	32.45	39.10	46.18	54.68	67.25	34.80	[13.3]
Number of Trades	103.1	0.14	56.94	93.42	111.1	118.9	135.1	78.17	[14.7]
Number of Trades Institutions	30.66	0.13	18.93	26.15	30.97	35.31	41.93	23.00	[14.6]
Bond Bid/Ask Spread	0.495	0.19	0.470	0.436	0.447	0.469	0.682	0.212	[10.8]
Bond Bid/Ask Spread Institutions	0.198	0.14	0.205	0.181	0.179	0.181	0.258	0.054	[8.4]
Bond Gamma	0.003	0.17	0.003	0.002	0.003	0.003	0.007	0.003	[6.4]
Number of Bonds Outstanding	37.90	0.00	37.83	30.81	32.75	39.84	48.30	10.47	[3.2]
Number of Days from Beginning of Month	2.907	-0.08	3.899	2.843	2.602	2.587	2.741	-1.158	[-9.9]
Number of Days from End of Month	2.743	-0.08	3.727	2.714	2.478	2.413	2.508	-1.219	[-10.6]
Bond Volatility	0.006	0.02	0.006	0.005	0.004	0.006	0.009	0.003	[6.2]
Bond Market Beta	0.880	0.05	1.006	0.825	0.738	0.731	1.129	0.123	[5.1]
Bond Value-at-Risk	0.033	0.27	0.035	0.028	0.026	0.029	0.054	0.020	[11.0]
Bond Institutional Ownership	51.91	-0.20	58.37	54.99	51.25	47.57	46.29	-12.08	[-28.3]
Distance to Default	9.488	-0.17	10.097	9.771	9.479	9.490	8.605	-1.492	[-15.9]
Nearness to Default	-9.488	0.17	-10.10	-9.77	-9.479	-9.490	-8.605	1.492	[15.9]
Investment Grade	0.863	-0.24	0.954	0.910	0.869	0.854	0.726	-0.227	[-19.3]
Non-Investment Grade	0.137	0.24	0.046	0.090	0.131	0.146	0.274	0.227	[19.3]
Bond Offering Price	99.49	0.05	99.23	99.49	99.55	99.61	99.56	0.331	[21.0]
Equity Mispricing	0.080	0.00	0.049	0.074	0.088	0.080	0.129	0.080	[3.9]
Equity Market Capitalization	42,720	-0.06	48,318	39,548	40,351	45,811	39,560	-8,758	[-7.4]
Equity Book/Market	0.652	0.20	0.591	0.601	0.604	0.640	0.825	0.234	[8.3]
Equity Beta	0.979	0.16	0.891	0.925	0.963	0.987	1.127	0.236	[16.3]
SUE	-0.003	-0.10	0.001	0.001	0.000	0.000	-0.016	-0.017	[-4.3]
Gross Profitability	0.226	-0.04	0.230	0.232	0.231	0.228	0.212	-0.018	[-5.2]
Earnings Yield	0.012	-0.28	0.056	0.053	0.047	0.038	-0.134	-0.190	[-11.0]
Equity Short-term Reversal	1.028	-0.03	1.067	1.061	1.051	1.053	0.910	-0.156	[-0.5]
Equity Momentum	10.59	-0.14	13.27	12.22	11.73	10.46	5.269	-8.002	[-10.6]
Equity Long-term Reversal	54.19	-0.10	58.54	58.03	56.28	54.01	44.13	-14.42	[-11.4]
Accruals	0.098	-0.03	0.093	0.105	0.112	0.107	0.077	-0.015	[-2.5]

(continued)

Table 2. Portfolio sorts by bond book-to-market *(continued)*

Panel B. Average portfolio returns

		All	Correlation	Bond Book/Market (BBM) Quintiles					Q5-Q1 (high BBM - low BBM)			
				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 Trades in Month t + 1		All	Correlation	Obs.	Bond Book/Market (BBM) Quintiles					Q5-Q1 (high BBM - low BBM)			
					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 Return in $t+1$	End Price of Bond Return in $t+1$	Bond Book/Market (BBM) Quintiles				
		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 capitalisation, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardised 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 capitalisation) 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 capitalisation 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 a 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)		Bond Return – Hedge Ratio * (Stock Return - 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 one-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- 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 three years), rating (credit rating), illiquidity (Bao et al. (2011) 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). Additionally, it reports alphas from a one-factor 'CAPM' model (alternatively from the WRDS returns of a value-weighted index of all corporate bonds and the martingale returns of the bonds in our sample), as well as two-factor versions that add equity HML to the CAPM factor. Standard error estimates use 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]	**
CAPM and CAPM + HML Models																		
Equal-weighted portfolios																		
Bond Market Index (Own Sample)	0.052	[0.85]		0.053	[1.25]		0.109	[4.03]	***	0.149	[4.16]	***	0.362	[3.44]	***	0.310	[2.11]	**
Bond Market Index (WRDS)	0.170	[2.52]	**	0.154	[3.41]	***	0.201	[5.85]	***	0.248	[6.08]	***	0.480	[4.83]	***	0.311	[2.39]	**
Bond Market Index (Own Sample) and Equity HML	0.053	[0.89]		0.057	[1.65]	*	0.110	[4.84]	***	0.152	[4.28]	***	0.381	[3.61]	***	0.328	[2.23]	**
Bond Market Index (WRDS) and Equity HML	0.164	[2.36]	**	0.152	[3.53]	***	0.197	[5.76]	***	0.245	[5.95]	***	0.492	[4.96]	***	0.328	[2.55]	**
Value-weighted portfolios																		
Bond Market Index (Own Sample)	-0.055	[-0.85]		-0.030	[-1.22]		0.009	[0.54]		0.027	[0.78]		0.237	[2.72]	***	0.292	[2.09]	**
Bond Market Index (WRDS)	0.083	[1.13]		0.084	[2.28]	**	0.114	[3.86]	***	0.137	[3.70]	***	0.371	[4.22]	***	0.288	[2.29]	**
Bond Market Index (Own Sample) and Equity HML	-0.058	[-0.91]		-0.032	[-1.38]		0.005	[0.33]		0.027	[0.78]		0.245	[2.81]	***	0.304	[2.19]	**
Bond Market Index (WRDS) and Equity HML	0.071	[0.93]		0.074	[1.92]	*	0.104	[3.55]	***	0.129	[3.83]	***	0.369	[4.42]	***	0.298	[2.44]	**

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 the negative of volume, the negative of the number of trades, the bond bid/ask spread, or the bond gamma 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 four 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 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	
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	

(continued)

Table 5. Default risk and liquidity interactions *(continued)*

Panel B. Liquidity (continued)

	(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 Gamma																								
Bond Book/Market Q5 * Bond Gamma Q5	0.159	[1.56]					0.150	[1.50]					0.182	[1.89]	*				0.177	[1.89]	*			
Bond Book/Market (normal score) * Bond Gamma Q5				0.072	[1.88]	*				0.071	[1.88]	*				0.069	[2.21]	**				0.070	[2.43]	**
Bond Book/Market Q5	0.394	[3.27]	***				0.390	[3.22]	***				0.151	[1.64]					0.189	[2.35]	**			
Bond Book/Market (normal score)				0.123	[2.92]	***				0.122	[2.87]	***				0.072	[1.55]					0.091	[2.35]	**
Bond Gamma Q5	0.029	[0.47]		0.145	[3.17]	***	0.033	[0.54]		0.138	[2.99]	***	-0.096	[-1.37]		-0.005	[-0.14]		-0.081	[-1.12]		-0.006	[-0.17]	
Observations	1,096			1,096			1,096			1,096			1,096			1,096			1,096			1,096		
Adj. R-Squared	0.13			0.12			0.13			0.13			0.27			0.27			0.31			0.31		
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 one-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 independently sort bonds into two categories based on bond size (market value outstanding) and three based on the BBM ratio. For bonds within each of the two size categories, we value-weight returns (based on bond size) in the two extreme BBM terciles, and calculate month $t + 1$'s return spread of the portfolio. We then average the two value-weighted return spreads to form Bond HML. 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 three years), rating (credit rating), illiquidity (the Bao et al. (2011) 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. 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 one-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 one-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 8. 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 9. 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 10. Buy-and-Hold returns

The table shows results from time series regressions of monthly bond portfolio returns (in excess of one-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 Bao et al. (2011) 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	
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 11. 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 Bao et al. (2011) 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 USD 100 000 (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]	**

Table 12. Bond return and alphas spreads from quintile sorts of gamma and BBM

The table reports the average return and alpha spreads between the extreme quintile bond book-to-market portfolios, when sorted into bond gamma quintiles (rows). To form the spread portfolios, each month, we independently sort bonds into 25 categories based on gamma illiquidity and bond book-to-market. For each gamma quintile, we compute the spread in the month $t+1$ equal- and value-weighted bond returns (based on bond value outstanding) between the top and bottom quintile of bond book-to-market bonds. To estimate alphas, we regress the return spreads on the bond market factor constructed using the WRDS bond returns and report the intercept. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % level, respectively.

	Equal-weighted Portfolios						Value-weighted Portfolios					
	Raw Returns			Bond Market Index (WRDS)			Raw Returns			Bond Market Index (WRDS)		
Gamma Quintile	Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat	
Q1 (Liquid)	0.271	[1.36]		0.038	[0.20]		0.280	[1.51]		0.077	[0.42]	
Q2	0.269	[1.95]	*	0.160	[0.93]		0.264	[1.75]	*	0.137	[0.78]	
Q3	0.404	[3.27]	***	0.260	[2.41]	**	0.447	[3.36]	***	0.316	[2.92]	***
Q4	0.421	[3.14]	***	0.281	[2.30]	**	0.451	[3.53]	***	0.309	[2.83]	***
Q5 (Illiquid)	0.505	[2.63]	***	0.245	[1.41]		0.541	[3.40]	***	0.352	[2.75]	***
Q5-Q1	0.234	[2.38]	**	0.207	[1.75]	*	0.260	[2.63]	***	0.275	[2.25]	**