NBER WORKING PAPER SERIES

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Söhnke M. Bartram
Mark Grinblatt
Yoshio Nozawa

Working Paper 27655
http://www.nber.org/papers/w27655

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2020, Revised May 2021

Helpful comments and suggestions by Hank Bessembinder, Michael Brennan, Jens Dick-Nielsen, Darrell Duffie, Andrea Eisfeldt, Eugene Fama, Valentin Haddad, Gergana Jostova, Owen Lamont, Francis Longstaff, Tyler Muir, Stavros Panageas, Alexander Philipov, Yves Rannou, Avanidhar Subrahmanyam, and seminar participants at the 2021 Frontiers of Factor Investing Conference, 2021 Eastern Finance Association Conference, 2021 European Economic Association Conference, 2021 European Finance Association Conference, 2021 French Finance Association, Coventry University, Two Sigma, UCLA, and University of Warwick are gratefully acknowledged. We thank the Center for Investing at HKUST, the Fink Center for Finance and Investments, the Price Center for Entrepreneurship and Innovation, the Ziman Center for Real Estate, and the Rosalinde and Arthur Gilbert Program in Real Estate, Finance and Urban Economics for generous funding. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 27655
August 2020, Revised May 2021
JEL No. G1,G11,G12,G14

ABSTRACT

Controlling for numerous attributes tied to default and priced asset risk, including yield, credit spread, bond rating, and maturity, we find that a corporate bond's book value divided by its market price strongly predicts its return. Bonds with the 20% highest "bond book-to-market ratios" outperform their lowest quintile counterparts by 3%-4% per year, other things equal. The rapid decay in the ratio's predictive efficacy with delay, the wide scope of the ratio's efficacy across the bond-type spectrum, and the insufficient ability of factor risk to account for the anomaly rejects the thesis that the corporate bond market is perfectly informationally efficient.

Söhnke M. Bartram
University of Warwick and CEPR
Warwick Business School
Finance Group
Coventry CV4 7AL
United Kingdom
s.m.bartram@wbs.ac.uk

Mark Grinblatt
Anderson School of Management
UCLA
110 Westwood Plaza
Los Angeles, CA 90095-1481
and NBER
mark.grinblatt@anderson.ucla.edu

Yoshio Nozawa
Lee Shau Kee Business Building
HKUST Business School
Clearwater Bay Road
Hong Kong, China
Sai Kung, NT
Hong Kong
nozawa@ust.hk

1 Introduction

One of modern finance's greatest puzzles is why the book-to-market ratio of a firm's equity plays such a central role in the cross-section of equity returns. One view is that the book-to-market ratio, a scaling of a firm's share price, proxies for priced risk. For example, Berk (1995) points out that high risk firms discount future cash flows at higher rates, implying that high risk firms should exhibit both low market prices and high book-to-market ratios other things equal. Thus, whenever alpha measurement imperfectly controls for risk, book-to-market will proxy for omitted risk factors and spuriously generate alpha.

An alternative and equally plausible explanation is that high book-to-market ratios reflect underpriced shares and low ratios reflect overpriced shares. This interpretation of book-to-market as a mispricing metric views book equity as a crude measure of equity fair value. Here, high book-to-market firms' high equity returns express rates that translate excessively low prices into future payoffs. A similar perspective, with time's arrow in reverse, is that share prices require irrationally high discount rates to undervalue the firm's future payoffs. If pricing mistakes rather than omitted risk factors account for the relation between book-to-market and returns, alpha's correlation with book-to-market warrants active trading that profits from investors' valuation errors.

To better understand book-to-market's role in asset pricing, we focus on another asset class: corporate bonds. This asset class rivals stocks in importance, yet little is known about its cross-section of returns. Book-to-market's importance in equity pricing makes the ratio a natural starting point for studying the drivers of corporate bond returns and the informational efficiency of the corporate bond market. The corporate bond market possesses unique attributes that aid understanding of why book-to-market influences asset returns, like equities. In contrast to equities, bond cash flow streams tend to be finite, are contractual, and of relatively shorter duration. These features make the magnitude and timing of bonds' future cash flows more transparent than those of equities. Indeed, the future cash flows of many bonds are known with relative certainty, as it is only the more extreme and infrequent outcomes for the economy or a company's prospects that materially affect the likelihood of the bonds' promised payments being made.

Given that the future cash flows of corporate bonds, particularly senior bonds, are far less risky than their equity counterparts, bond price movements have to arise largely from discount rate variation rather than from changes in projections of future cash flows. Thus, our key finding—that a bond book-to-market signal generates risk-adjusted bond alphas that are almost as large as the alphas equity book-to-market generates for stocks—favors mispricing over risk mismeasurement as the better explanation of the book-to-market phenomenon. Even with bonds for which asset risk plays a larger role, the bond researcher has control variables like yield-to-maturity ("YTM"), credit spread, duration, and default risk estimates that are far superior to the risk controls available for equity analysis. Such superior risk controls buttress mispricing as the better explanation of our findings.

We define the "bond book-to-market ratio" ("BBM") as the bond's book (or carrying) value per unit of face amount divided by the bond's market price per unit of face amount. At the time a bond is issued, BBM starts at one. Indeed, for most bonds, the coupons are set so that a bond's book value at issue and face amount paid at maturity are approximately the same—referred to as a par bond if the two amounts are identical. Over time, the book-to-market ratios of formerly par bonds then rise above one (becoming discount bonds) or fall below one (premium bonds). Likewise, bonds issued at discounts or premia evolve to have greater or lesser discounts and premia than their amortization schedules would indicate. As with par bond issues, changing economic forces and perhaps sentiment generate price deviations from those schedules. If sentiment plays any role, it tends to mean revert. Hence, low book-to-market ratios that are driven by optimistic sentiment tend to rise, making risk-adjusted returns abnormally low. Likewise, sentiment-driven high book-to-market ratios tend to fall, making returns abnormally high. The abnormal returns generated by sentiment's tendency to mean revert generates bond prices with proclivities to converge towards their fair values.

Most of BBM's variation depends on a bond's price path since issuance. If the price path has generated returns that closely maintain the bond's initial yield-to-maturity, BBM remains close to one. However, if the bond's return has exceeded its initial yield-to-maturity, its past return will be high, and its yield-to-maturity will fall. What is noteworthy about BBM's ability to predict bond returns is that it survives controls that also influence returns, including past returns, duration, credit spread, yield-to-maturity, and default likelihood.

The yield-to-maturity, like BBM, is a transformation of a bond's price. At issuance, the YTM of the far more common "par bonds" is close to the bond's coupon rate, but YTM evolves like BBM to differ from its initial value. Neither yield-to-maturity nor bond book-to-market directly measure an expected return. However, one expects differences in bonds' YTMs—particularly when yield is deployed as a set of rank-based dummy variables—to better map into expected returns than their corresponding differences in the cruder BBM ratio. Nevertheless, when controlling for YTM ranks in this fashion along with a host of other variables, including credit rating, duration, credit spread, coupon rate, and characteristics that influence equity returns, the highest BBM bond quintile outperforms the lowest by almost 4% per year.[1]

A primary deterrent to the study of corporate bond is their relatively thin trading. While many corporate bonds trade more than once per day, quite a few do not trade for days or even weeks at a time. We apply the martingale property of informationally efficient asset prices to overcome the obstacle of infrequent trading. This property enables imputation of the hypothetical mid-market prices one would trade at from transactions on other dates. While the imputed prices represent noisy estimates, the low volatility of bonds offsets the enhanced return noise from measurement error, facilitating detection of significant pricing inefficiencies.

The risk-adjusted profits from the monthly-rebalanced BBM signal do not survive transaction costs, which are substantially higher in the corporate bond market than in the stock market. These transaction costs remain an obstacle for hedge funds and other short-term arbitrageurs, whether we estimate these costs from the prices of all trades between dealers and customers or from those with volumes exceeding 100,000 U.S. dollars. Nevertheless, a buy-and-hold variation of the strategy does survive the transaction costs incurred by larger transaction sizes, enhancing overall net performance provided the institutions avoid additional short sales costs and constraints, for instance by tilting a long-only portfolio towards underpriced and away from overpriced bonds to some degree.

[1] Israel, Palhares, and Richardson (2018) refer to the YTM spread between a bond and similar credit risk bonds as "value." Our BBM "value" anomaly controls for YTM, credit spread, and credit risk, and its magnitude is invariant to credit rating.

Alongside an abundant 50-year literature on equity market efficiency[2] is a sparse understanding of the informational efficiency of the bond market, which is fundamental to a comprehensive portrait of asset pricing. For U.S. government bonds, research on information efficiency includes Fama and Bliss (1987) and Cochrane and Piazzesi (2005), who show that a linear combination of forward rates predicts the returns of bonds at various maturities, while Joslin, Priebsch and Singleton (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, Moskowitz, and Pedersen (2013) uncover value and momentum effects in government bond indices, while Brooks and Moskowitz (2017) find that value, momentum and carry factors help predict government bond returns outside of the United States. Finally, Brooks, Gould, and Richardson (2020) show that exposure to traditional risk factors largely explains the active returns of fixed income managers.

Research on whether corporate bonds reflect public information and on corporate bond characteristics that account for the cross-section of corporate bond returns is nascent. Gebhardt, Hvidkjaer, and Swaminathan (2005) report that bonds with higher default risk earn 7 bp higher monthly returns than those with low default risk, and bonds with long times to maturity earn 4 bp more per month than those with short maturities. Chordia et al. (2017), Jostova et al. (2013), Bai, Bali and Wen (2019), and Bali, Subramanyam, and Wen (2019) show that bond returns are correlated with past bond returns. Choi and Kim (2018), Avramov et al. (2019), and Bali et al. (2020) study common anomalies in bond and equity markets, while Israel, Palhares and Richardson (2018) and Kelly et al. (2020) document risk factors in corporate bond returns. Bretscher et al. (2020) show that corporate finance puzzles are resolved with better estimates of firms' market capital structure. A portion of the research has taken place after ours and none focuses on BBM and mispricing.

Fundamental differences between corporate equity and corporate bond markets could have ramifications for the relative efficiency of these two financial markets. On the one hand, corporate bond prices may be

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[2] Most equity studies relate return premia to firm characteristics (or factors derived from them), including 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, Karolyi, and Kho, 2011), profitability (Novy-Marx, 2013), and mispricing from peer-implied accounting statement and equity market capitalizations (Bartram and Grinblatt, 2018, 2021). Harvey, Liu, and Zhu (2016) and Green, Hand, and Zhang (2013) document more than 300 stock return predictors.

more efficient than their equity counterparts due to the more sophisticated institutional investor base that dominates bond trading. Alternatively, the corporate bond market may be less efficient due to its differing (primarily over-the-counter) market structure. Such over-the-counter trading likely engenders greater transaction costs and less pre-trade price transparency, preventing arbitrageurs from correcting mispricing. Corporate bonds also tend to trade with less liquidity than stocks, and they are held for long periods by their primary investors: pension funds, insurance companies, endowments, and mutual funds.

We employ two different approaches to estimate bond trading profits adjusted for risk. Our primary approach utilizes cross-sectional Fama and MacBeth (1973) regressions. These regressions control for bond characteristics, such as yield-to-maturity, bond credit ratings, nearness to default, duration, credit spread, coupon, maturity, and bond past returns, among others. They also control for several equity characteristics tied to the cross section of equity returns—among them, equity book-to-market, accruals, earnings yield, gross profitability, and several market microstructure controls. As a robustness check, we also study whether the abnormal returns of the BBM signal can be explained by factor models. Here, we use the factor model of Bai, Bali and Wen (2019, BBW), or a variation of BBW's factors that is augmented by a term structure factor. After controlling for these risk factors, the profits to the BBM strategy remain economically and statistically significant, both for equal- and value-weighted bond portfolios.

The risk-adjusted profits we document are not contaminated by market microstructure effects or by favorable pricing available only for certain types of investors or trades. Our strategy's profits are also not due to the long-term return reversal effect of Bali, Subrahmanyam, and Wen (2019). For the 20% of bonds that are closest to default, the BBM signal has about the same efficacy as it does for the remaining 80%. The irrelevance of default risk for BBM efficacy casts doubt on the omitted risk factor explanation of the BBM anomaly. Moreover, for government bonds, BBM offers no return predictability, indicating that our controls are adequate for capturing the return effects of the term structure. Finally, we show that the efficacy of the BBM signal for corporate bonds decays rapidly as the signal becomes stale. The rapid decay in efficacy—particularly when compared to the slower evolution of the BBM attribute—is also more suggestive of mispricing rather than risk mismeasurement as the source of the BBM anomaly.

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

Our sample of signals and bond returns—derived from transaction prices on the Trade Reporting and Compliance Engine (TRACE) database—is extensive. It comprises 212 calendar months from January 2003 to August 2020 for trading signals, and from February 2003 to September 2020 for returns, covering 8,925 different bonds, 838 firms, and 459,040 bond-month observations.[3] The large sample is facilitated by a methodological contribution—applying the martingale property to construct monthly returns when trading is thin and, to avoid biased inference, signals requiring a time gap from return periods. Prior studies employing TRACE largely focus on its most liquid bonds. It is fairly straightforward to construct monthly returns for bonds that trade nearly every day, often multiple times. However, studies of such bonds cannot easily draw unbiased conclusions since liquidity could be correlated with returns, or liquidity may affect correlations of bond returns with other variables. Hence, filtering a sample for its most liquid bonds could lead to conclusions that do not even apply to the narrow set of bonds studied. By contrast, analysis of liquidity's impact here suggests that our conclusions are, if anything, conservative.[4] We also are more conservative than prior studies in separating the date of the signal from the date at which trade execution prices are revealed. Using a minimum of seven days separation between signal and execution price prevents trade splitting in illiquid bonds from contaminating our findings.

[3] While TRACE data commence in July 2002, our performance analysis commences February 2003 to ensure data on the bond momentum control in Fama-MacBeth regressions.

[4] Most prior corporate bond research applies filters that censor the bond sample or use model prices or compute returns with traders' models/quotes rather than transaction prices. For example, Chordia et al. (2017) use a mix of dealer quotes and bonds in TRACE that trade in the last 5 trading days of the month. Bao et al. (2011) sample require a bond to trade at least 75% of its relevant business days. Israel et al. (2018) select a single monthly representative bond for each issuer based on bond 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 days (or, for a surprising number, even weeks), indices are partly built around mid-spread marks of traders' credit risk models that are divorced from nearby transactions.

Next, Section 2 describes the data and methodology used. Section 3 presents the main empirical results. Section 4 analyzes whether mispricing or defective risk measurement better explains the BBM anomaly. Section 5 studies whether BBM proxies for the BG mispricing signal, whether a BBM effect exists for a larger cross-section of corporate bonds (including junior and puttable bonds), whether the prices used for order execution at are available to all or only some market participants, and whether a BBM trading strategy can be implemented at low transaction costs. Section 6 concludes the paper.

2 Data and Methodology

We analyze the profitability in month $t + 1$ of trading signals, primarily BBM, formulated in month t. After describing data and filters sourced from the transaction data in the enhanced TRACE database, we discuss the construction of monthly signals and bond returns for each corporate bond in our sample.

2.1 Data Sources and Filters

The sample is initially limited to USD-denominated, senior, unsecured corporate bonds issued by U.S. domiciled non-financial firms with no embedded options other than call provisions. (Robustness tests later study all corporate bonds with fixed coupon rates in TRACE.) We exclude cancelled transactions, those that TRACE specifies as occurring before the issue date or after the maturity date of a bond, and transactions in the bonds of financial firms (SIC codes 60-69). We modify prices (or any other trade terms) to be TRACE's corrected values when TRACE indicates the trading counterparties retroactively corrected the prices (or terms). Following BBW (2019), we also remove observations with a transaction price 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 the signal. For the BG signal, on the transaction day that provides the trading signal, the issuing firm must be in the Center for Research in Security Prices' (CRSP) Monthly Stock File as the only common equity share class of a U.S. corporation (share classes 10 and 11), and be listed on NYSE, Amex or Nasdaq (exchange codes 1-3) with a share price of at least $5, positive total assets, and a positive number of common shares outstanding.

2.2 Return Construction

Bonds, unlike equities, trade infrequently and often at large bid-ask spreads. To address these two issues, we apply the martingale property of asset pricing. According to this property, an unbiased estimate of an asset's price on some date is its transaction price at some other date, adjusted for time's impact due to the accumulation of risk premia, the riskless time value of money, and any payouts. These adjustments are small and closely captured by the bond's interest earned when the transaction date is close to the desired price estimation date.

TRACE reports bond transactions' "flat" (or equivalently "clean") prices. Unless a bond is in default, these flat prices are not the transaction prices one pays for a bond. Instead, one pays the sum of the flat price and interest accrued. While daily, weekly, or monthly changes in accrued interest plus any distributions do not perfectly match the compensation for the time value of money and risk, they are close approximations, particularly over short time periods. Hence, for almost all bonds, the flat price of a bond approximately follows a martingale—validating substitution of flat prices from transactions in a bond at nearby dates for the flat prices that would be experienced on days without transactions in the same bond.

End-of-month Flat Bond Prices. The martingale property implies that the end-of-month flat bond prices we estimate, P^E, are the mid-market end-of-month flat prices at which the bonds would trade plus noise. The noise, which we try to minimize, depends on bond price volatility between the date of the transaction used for estimation and the end of the month, as well as the spread charged by the transacting party (bond seller or buyer) who provides liquidity. For bond j's end-of-month $t + 1$ flat price, we use the flat price of the last bond j transaction in month $t + 1$. For example, to obtain the end-of-April 2013 flat price of a bond, we might use the flat price of an April 26, 2013 trade. Thus, the estimated end-of-month prices derive from transaction dates that differ depending on when a particular bond last traded. If there is no month $t + 1$ transaction for bond j, we treat the bond's end-of-month $t + 1$ price as missing.

Beginning-of-month Flat Bond Prices. Like the end-of-month bond price, we estimate each bond's beginning-of-month flat prices, P^B, as the flat first transaction price of the month. Thus, a bond's March 2013 beginning-of-month price has to come from a March 2013 trade. If the bond does not trade in the month, its beginning-of-month price is missing. 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 accrued or paid interest.

Monthly Bond-level Returns. Using the end-of-month and beginning-of-month flat bond price estimates described above, we construct month $t + 1$ returns as:

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

where P^{B}_{t+1} is the estimated beginning-of-month $t + 1$ flat price, P^{E}_{t+1} is the estimated end-of-month $t + 1$ flat price, AI_{t+1} is the accrued interest owed at the end of month $t + 1$, and C_{t+1} is the coupon of the bond (if any) awarded to investors holding the bond in month $t + 1$. We consider the returns in two consecutive months to be missing if their product is less than –0.04. (A 20% monthly price increase followed by more than 20% decrease, or the reverse, likely reflects false recording of a price used to compute one or more of the returns.). Cumulated returns over six months, used for a momentum control variable, are computed analogously to equation (1). The return is computed from a single beginning and ending price over the past return horizon. As in equation (1), the return is adjusted for beginning and ending accrued interest (to convert the estimated flat price into a price paid for the transaction), as well as any coupons paid during the interval.

Note that the prices in the numerator and denominator are noisy estimates of the flat prices we would observe if trades occurred at the end of each month. Due to Jensen's inequality, noise in the denominator upwardly biases equation (1)'s return estimates—analogous to the upward bias in equity returns shown in Blume and Stambaugh (1983). However, our results are based on the return spread between two quintile portfolios. If the bias affects the long and short legs of portfolios in the same way, it is eliminated by looking at their return spread. Alternatively, if the bias is greater in the short leg (as implied by evidence on trading frequency), our alpha spreads underestimate the true alpha spreads and are therefore conservative.

Separate from this issue is the effect of scaling for the time horizon. Note that we do not rescale reported monthly returns to cover a full month. The fact that equation (1)'s reported returns are derived from flat prices that cover less than one full month does not bias reported monthly and annualized returns per se (for bonds issued exactly at par). On average, these flat prices follow a martingale, and equation (1)'s accrued interest covers the entire month. However, because our BBM bond portfolios contain bond with less-than full month returns, reported monthly alphas tend to be understated in absolute terms. The scaling issue implies that reported monthly alphas are conservative if positive and more negative than reported if negative.

The sample omits bonds in default at the time a trading signal is received (month t). However, it includes bonds that commence default in the month our strategies invest in them ($t + 1$) to avoid data censorship. 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, transaction prices, and thus the flat prices of defaulted bonds, do not follow a martingale process—motivating adjustment of their beginning- and end-of-month price estimates. The adjustment we apply deliberately underestimates defaulted bonds' returns, thus making our return spread estimates conservative because there are no defaulted bonds in our strategies' short positions.[5] The conservative approach is "overkill," as transactions in bonds that commence default in month $t + 1$ are quite rare, even for the strategies' long positions—constituting only 0.02% of their transactions.

A similarly rare situation, where we opt for no modification, exists for the few bonds that are issued at deep discounts. Fewer than 0.1% of bonds have offering prices of less than 50, and 99.8% have offering prices above 90. Moreover, the average issue prices of the five BBM quintile portfolios are all close to 99.5. The flat prices of such original issue discount bonds appreciate rather than (approximately) follow a martingale. Ignoring the original issue discount upwardly biases equation (1)'s denominator as an estimate of the true purchase price. However, sizable discounts are rare, and the numbers of days of amortization are generally small. For these reasons, adjusting the martingale price estimate for original issue discount bonds increases the returns of BBM quintile portfolios by only negligible amounts. The adjustment is eschewed because it has no detectable effect on the return difference between any pair of quintile portfolios.

[5] Specifically, if the transaction price used for the beginning-of-month price is quoted flat due to default, we substitute the flat price of the first transaction preceding the transaction price used for the signal as P^B in equation (1)'s denominator and the nearest to end-of-month post-default transaction price for P^E in equation (1) and do not add accrued interest or a coupon in the numerator. This understates the return for the quintile portfolio we take a long position in and has no effect on the short position (which lacks defaulted bonds).

2.3 Signal Construction

Our trading signals, largely BBM, utilize the market prices of transactions, as do the returns described above. Hence, measurement error in a bond's market price that affects both its month t signal and its month $t + 1$ return would cause spurious correlation between the two. To avoid this measurement pitfall, and unlike other studies, we construct a month t trading signal from prices of transactions occurring in month t that are at least seven calendar days prior to the end of the month.[6] We then estimate month $t + 1$ returns with the procedure described in Section 2.2. Signals constructed in this fashion cannot correlate with the estimated return for the next month: both the beginning- and end-of-month transaction prices are formed at least seven days after the signal is publicly known. This procedure generates a tradable strategy that allows the month $t+1$ return to be as close to a full month return as possible.

Bond Book-to-Market Signal. The book value per $100 face amount is an adjustment of the issue price of the bond, sourced from the Mergent Fixed Income Securities Database (FISD). The distribution of issue prices can be seen in Table 1 Panel A. For most bonds, the FISD issue price is close to $100.[7] If the bond is issued at a discount or premium, we apply the accounting rule that linearly amortizes the premium or discount to maturity on the month-end dates to arrive at the bond's current book value for the end of month t. In the approximately 30% of cases where FISD lacks the issue price, we omit the bond as a candidate for a potential trade.[8]

Our month t BBM signal is Book/P^S, the reciprocal of the flat price of the bond per dollar of book amount. The signal's flat price per $100 of face amount, P^S, is taken from the bond's most recent transaction, excluding transactions within six calendar days before the end of month t. Hence, a BBM signal to trade at the end of June 2015 could be based on a transaction from February 2015. Table 1 Panel B reports the distribution

[6] To illustrate, if a signal used the last month t transaction price to predict bond returns in month $t + 1$, and the latter returns depended on the same month-t price due to trade splitting and workouts over a few days, market microstructure noise (such as bid-ask bounce) could artificially generate return predictability in the absence of the seven-day gap.

[7] The BBM signal's ability to predict returns is highly significant, but slightly reduced, if 100 is substituted for the Mergent issue price of the bonds.

[8] With all controls in Fama MacBeth regressions, the return spread between the Q5 and Q1 BBM portfolios is 32 bp per month for the FISD subsample we focus on in the paper, but 25 bp for the subsample lacking FISD issue price data. For the FISD-deficient subsample, 100 replaces book value.

of time between the signal formation transaction (the source for P^S in Book/P^S) and the transaction that determines the beginning-of-period price used to construct the bond's return in month $t + 1$. For the senior unsecured bonds that researchers traditionally study (e.g., BBW, 2019; Chung, Wang, and Wu, 2019) and that we focus on, the median gap between the signal date and that latter price is 11 days, while the average is 16 days (first row). About 7% of these observations have a gap exceeding one month. 99% of the observations for the BBM signal reflect transactions with one- to thirteen-week gaps from the end of the month.

Figure 1 depicts the transaction timing of the prices used for signal and return construction. P^S represents the transaction price used for the book-to-market signal in month t, P^B is the beginning price for the return in month $t + 1$, and P^E is the end price for the return in month $t + 1$. It illustrates three consecutive transactions in the bond. While Figure 1 shows P^S as originating in month t, it could have come from a prior month if there is no qualifying bond transaction in month t. The beginning and ending prices for month $t + 1$ returns come from transactions in that month (which could be a single transaction).

Bartram and Grinblatt Mispricing Signal. A later robustness check studies whether a bond-centric implementation of BG's (2018) mispricing measure generates a signal that predicts a bond's future return and subsumes the BBM signal. Each bond is assigned a firm-level BG mispricing measure. The BG signal first computes an estimated month t market value of each firm's total liabilities—including bonds and other debt obligations (e.g., commercial paper, accounts payable, bank loans) that lack TRACE-reported transactions. Our estimate of the month t market value of firm i's total liabilities, $V_{i,t}$, is the sum of the market capitalization of its bonds, computed from their most recent TRACE transaction prices (excluding the last 7 calendar days of a month), plus the aggregate book value of firm i's other liabilities.

The BG bond mispricing signal, a metric of the degree to which each firm's aggregate debt obligations are under- or overvalued, is derived from monthly cross-sectional regressions of $V_{i,t}$ on firm i's 28 most commonly reported items in Compustat's point-in-time accounting database as of month t. The regression predictions—essentially peer-implied norms for $V_{i,t}$ implicit in all firms' accounting data—represent month t fair values for each firm's total liabilities.[9] We then assign to each bond the BG mispricing signal of its issuing firm, which is the percentage deviation of the firm's predicted $V_{i,t}$ from its actual value. In contrast to month *t*'s market capitalization estimate used to construct the firm-based signal, the instrument level trading strategy uses only bonds for which we can compute month $t + 1$ returns with Section 2.2's procedures.

2.4 Alpha Tests for Signal Efficacy and Control Variables

The BBM and BG signals sort bonds into quintiles at the end of month *t*, with quintile 5 having the most value-oriented bonds (BBM signal) or most underpriced bonds (BG signal). We then analyze month $t + 1$ bond returns within these quintile portfolios. Our primary tests for the alpha generating efficacy of the signals employ Fama and MacBeth (1973, FM) cross-sectional regressions. We also study factor models.

FM Regressions. Here, the month *t* regression's unit of analysis is the bond. We cross-sectionally regress a bond's month $t + 1$ return (computed with Section 2.2's procedures) on quintile rank dummies or normal scores computed from BBM and numerous control variables. The coefficients on each regressor are then averaged across months. The controls consist of bond characteristics and issuing firms' equity characteristics measured as close to the end of month *t* as possible. They include each bond's coupon rate, yield-to-maturity, credit spread, credit rating, value outstanding, time to maturity, duration, age, past 7-month return excluding prior month ("bond momentum"), past 1-month return ("bond reversal"), bid-ask spread, and nearness-to-default. The controls also include equity characteristics, including equity market beta, equity market capitalization, equity book-to-market, past 1-month stock return ("short-term reversal"), past 5-year stock return excluding the prior year ("long-term reversal"), past 12-month stock return excluding prior month ("momentum"), accruals, earnings momentum, gross profitability, and earnings yield. Most of the FM regressions also include market microstructure controls that are measured in the return period, month $t + 1$. We employ four main specifications of regression controls. The first has no controls, the second has market microstructure controls; the third has controls for bond characteristics as well as market microstructure controls; the fourth controls for

[9] These 28 items, listed in Appendix A, are the same regressors used in BG's (2018) equity signal. Point-in-time data ensure that the information used to estimate debt fair value was available to market participants at the point in time when the mispricing signal motivates a trade.

bond and market microstructure characteristics, along with equity characteristics of the bond issuer. Appendix A describes the characteristics in more detail. A robustness check with a necessarily shortened sample period and smaller cross-section includes the bond's past 3-year return skipping a year ("bond long-term reversal"). The analysis of the BG strategy is analogous. Here we assign each of the bonds an attribute that is identical to its firms' BG signal.

Factor Model Time Series Regressions. We also control for risk by regressing the time series of returns of five BBM quintile portfolios in excess of LIBOR on the five bond factors of BBW (2019): the bond market, credit risk, downside risk, liquidity risk, and reversal factors.[10] We refer to this risk model as the "BBW" factor model. We construct these factors using bond return data from TRACE following the procedures described in BBW (2019).[11] We use data from Merrill Lynch to construct the downside risk measure (the second worst return in the previous three years) for the first three years of our sample, a subperiod when TRACE lacks the needed prior-year data to compute the factor. In addition, we use an Augmented BBW 6-factor model that further adds a term structure factor to the 5-factor BBW model popularized in the literature.

2.5 Summary Statistics for the Overall Sample

Table 2 Panel A reports summary statistics for BBM and other characteristics of the senior unsecured bonds and their issuing firms. Each row reports the time series average of cross-sectional means of each variable using

[10] As a robustness test, we also estimate alphas using a 21-factor model comprising 13 equity factors and eight bond market factors. The equity market factors are all five equity factors of the Fama and French (2014) model, i.e., market excess return, size, book-to-market, profitability, and investment; three equity past-return factors: short-term reversal, momentum, and long-term reversal, all sourced from the Kenneth French data library; and finally, the excess returns of the equity of the bonds in the five BBM quintiles. The eight bond market factors consist of two bond factors for the default spread and term spread, used in Chordia et al. (2017); two factors, bond momentum and bond value, as computed from government bonds in Asness, Moskowitz, and Pedersen (2013), and four excess return factors (above the risk-free rate) tied to bond indices from DataStream: U.S. Treasury Intermediate Index, U.S. Long-Term Treasury Index, U.S. Corporate Investment Grade Index, and the U.S. Corporate High-Yield Index. The indices measure growth in investment values including price changes, coupon payments and changes in accrued interests for the underlying bond portfolios. The resulting BBM alpha spreads are greater than those using the BBW factor model.

[11] Specifically, we calculate the volume-weighted average prices at the daily frequency, and build a monthly return considering two scenarios: first, if a bond price in the last five business days in month t and $t + 1$ is available, then we calculate a return using the last daily price in those months; second, if a return in the first scenario is not available, then we use the first daily price in the first five business days in month $t + 1$ to the last daily price in the last five business days. If neither is available, we treat month $t + 1$ return as missing. Using Mergent FISD, we narrow down on the subsets of bonds described in BBW (2019). Finally, we follow them to value-weight bonds using face values rather than market values in forming the factors, though our value-weighted BBM portfolios are based on market values.

all bonds (first column) and the bonds within each BBM quintile (third to seventh column). Q1 represents bonds with the smallest 20% of BBM, averaging a BBM of 0.85; Q5 represents the highest BBM quintile, averaging a BBM of 1.10. The panel also reports the time series average of the cross-sectional correlations of the characteristic with BBM (second column).

The BG bond mispricing signal, with an average correlation of 0.29, positively correlates with BBM and monotonically increases across BBM quintiles. Many other characteristics also correlate with BBM. High BBM bonds tend to have poorer S&P credit ratings (AAA=1, …, D=22, with 10 or less indicating investment grade) and are closer to default.[12] They also have higher YTMs, lower market values, higher bid-ask spreads, and been issued more recently. Lastly, they come from firms with higher equity beta, poorer returns over the past year, larger equity book-to-market, and lower earnings/stock price ratios. By contrast, the lowest quintile of BBM bonds have the highest returns over the past six months (bond momentum, as used in prior research). These bonds also come from firms with the highest stock returns over the past year (equity momentum) and are attached to larger firms.[13] Bond maturity and duration, while concentrated in the two extreme BBM quintiles, are far greatest within the 20% lowest BBM bonds. Combined with the fact that lower credit risk tends to extend the effective maturity of actual bond payments, and holding coupon rate the same (which has opposing duration and tax effects on expected returns), it is apparent that the greatest risk from shifts in the risk-free term structure lie within the 20% lowest BBM bonds, which the BBM strategy sells.

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 two rows correspond to equal- (EW) and value- (VW) weighted quintile portfolio returns, respectively, both of which exhibit nearly monotonic increases across BBM quintiles. For example, the lowest BBM EW quintile portfolio earns 57 bp per month, while the highest earns 101 bp per month. Panel B

[12] Because these are senior bonds, their default risk is relatively low, even for the highest BBM quintile, which averages to an investment grade rating. We also employ nearness to default (the negative of the distance to default measure by Schaefer and Strebulaev, 2008). Nearness to default is the *z*-value corresponding to the default probability from an adaptation of the Black-Scholes model. Quintiles for nearness to default are thus identical to quintiles for default probability. The firm is in default when nearness to default is positive infinity, and the default probability is less than one-half when nearness to default is negative.

[13] Nozawa (2017) and Chordia et al. (2017) show that most corporate bonds are issued by large firms (i.e., with market capitalization above the NYSE 50th percentile).

also shows the average monthly return for the full sample (66 bp EW and 57 bp VW), 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 TRACE data also indicate whether a transaction is a dealer buy from a customer (at a "bid price"), a dealer sale to a customer (at an "ask price"), or a dealer-to-dealer transaction. Table 2 Panel C reports each BBM quintile's fraction of transactions used for the beginning price of month $t + 1$'s return that is a bid price (dealer buy from a customer), an ask price (dealer sell to a customer), or at a price negotiated between two dealers. If the return initiating transactions in quintile 5 were relatively more likely to be bid prices than the transactions in quintile 1, the return pattern in Panel B could be due to market microstructure effects. However, the opposite is true. Compared to quintile 1, transactions initiating quintile 5 are relatively more likely to be ask prices. This suggests that the extreme quintile return spread in Panel B is a conservative estimate of the true quintile spread between mid-market valuations. We later investigate whether other potential sources of price distortions can account for that spread. In particular, we address whether dealer charges for supplying liquidity to customers could account for the return pattern across quintiles.

The results in Table 2 indicate that both the EW and VW annualized return spreads between the extreme BBM quintiles are about 5% per year. While the relatively low volatility of bond returns makes a 5% spread look large, many bond and firm attributes that influence returns correlate with BBM. For this reason, we need to analyze the marginal effect of BBM controlling for these other attributes.

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

We now investigate whether BBM contains return-relevant information that is distinct from other known predictors of securities' returns. Both cross-sectional FM regressions and time series factor model regressions show that BBM is not a proxy for commonly used characteristics or risk attributes that predict return premia.

3.1 Fama-MacBeth Cross-Sectional Regressions

The FM approach regresses next month's bond return (in percentage form) cross-sectionally on the BBM signal and other lagged bond and equity characteristics:

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

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 Fama-MacBeth procedure averages the monthly coefficients over time and tests whether the average significantly differs from zero.

To assess the economic magnitudes of BBM and other predictors, Table 3's four odd-numbered specifications transform all exogenous variables into five quintile dummies Q1, …, Q5 and regress bond returns on dummy variables corresponding to Q2 through Q5, with Q1 omitted due to the regression intercept. For brevity, Table 3 only reports the coefficients for the Q5 dummy variables. Even-numbered 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 a set of market microstructure controls to Specifications 1 and 2, which 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 that trade in month $t + 1$, the percentage of the market value of the issuing firm's bonds that trade in month $t + 1$ as a fraction of the market value of the firm's bonds with signals in month t, 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. These include quintile dummy variables for the bond's coupon rate, yield-to-maturity, credit spread, market capitalization (bond value), age, time to maturity, duration, bid-ask spread, past returns (over short and intermediate horizons), credit rating, and the firm's nearness-to-default. These bond-specific controls are rooted in the finance literature cited earlier. Finally, "kitchen sink" Specifications 7 and 8 add equity and firm characteristics to Specifications 5 and 6. These include the equity beta, equity market capitalization, equity book-to-market, and past equity returns (at 3 horizons) of the issuing firm, as well as its accruals, earnings surprises, gross profitability, and earning yield, which have all been studied in the finance literature.[14]

All specifications tell a similar story about BBM's importance for the cross-section of bond returns. Specification 1 shows that BBM Quintile 5 bonds outperform Q1 bonds by an average of 44 bp per month (t = 3.62), controlling for industry fixed effects. The coefficient of 0.14 on the parametric BBM signal is also significant (t = 3.13) as Specification 2 shows. Specifications 3 and 4 illustrate that the market microstructure controls have little effect on the results: BBM's average coefficient is virtually the same, whether comparing Specification 3 with 1, or 4 with 2. Although not reported for brevity, the relatively small effect of the market microstructure regressors applies to the remaining two specifications as well. This suggests that our martingale procedure for identifying month $t + 1$ returns is unlikely to have altered what might be inferred if corporate bonds traded far more frequently.[15] The addition of bond-specific controls (in Specifications 5 and 6), measured (in contrast to the signal's seven day gap) as closely to the end of month t as possible, reduces BBM's influence on a bond's month $t + 1$ return by about 40%, but the BBM effect remains highly significant. Specifications 7 and 8's addition of controls known to be related to equity returns increases the BBM coefficients by about 20% compared to Specifications 5 and 6 and also increases their significance. Specifications 7 and 8 also establish

[14] See Banz (1979) and Fama and French (1992) for size, Rosenberg, Reid, and Lanstein (1985) for book-to-market, Jegadeesh (1990) and Jegadeesh and Titman (1993) for past returns, Sloan (1996) for accruals, Chordia and Shivakumar (2006) for earnings surprise, Novy-Marx (2013) for gross profitability, and Basu (1983) and Haugen and Baker (1996) for earnings yield. BG (2018, 2021) use the same set of equity controls in their FM regressions

[15] We also considered other sources of liquidity-related biases. For example, bonds tend to be called by their issuing firms when their fair value (in the absence of a call) exceeds the call price. Could superior unobserved returns for bonds that would otherwise be classified as BBM Q1 bonds be filtered out, biasing the Q1 portfolio returns downward? We tested this hypothesis, both by filtering out bond returns in months approaching call dates and by adding controls for bond call dates. However, (in unreported results) our statistical tests suggest callability has little effect on the BBM alpha spread. Alternatively, if dealers price-discriminate, we may be confounding the BBM anomaly with persistent client-favorable prices that only certain clients can trade at. However, if client-specific price deviations persist beyond our 7-day minimum gap (and, on average, about a 2-week gap) between the BBM signal transaction date and the transaction date used for the beginning price of next month's return, the signal month's return spread across BBM quintiles should be of comparable magnitude to the spread in the return month. Similarly, if we break any persistence in the client trades we use, by forming signals only from (often more distant) dealer-to-dealer transactions, our BBM spreads should weaken substantially. Neither of these implications hold. The difference in returns between BBM Q5 and Q1 bonds is –15 bp in signal month t (Table 2 Panel A), while +44 bp in month $t + 1$ (Table 2 Panel B). Similarly, the BBM return and alpha spreads (irrespective of controls) are stronger with dealer-to-dealer trades as the sole source of the BBM signal.

that equity book-to-market, despite its correlation with BBM, does not predict bond returns once BBM is controlled for.[16]

Our use of quintile dummies for these controls allows flexibility in the relationship between the control variables' parametric values and returns. For example, bond expected returns tend to be concave functions of yield-to-maturity as promises of very high yields are less likely to be met than promises of lower yields. Likewise, depending on the month, the term structure can be upward sloping, downward sloping, or hump shaped. Expressing the control regressors as nonparametric quintile dummies captures the dynamic and nonlinear relationship between the controls and expected returns more accurately.

So, how strong are these results? Compared to equity returns, bond returns have far lower cross-sectional volatility and predominantly come from transactions associated with larger firms, making the size of the BBM anomaly relatively more impressive. Moreover, compared to its equity cousin, the BBM effect has far superior risk controls. In addition to quintile dummies for yield-to-maturity, default risk, bond age, and liquidity, equation (2)'s cross-sectional regressions control for the effect of maturity and industry. In light of these controls and the CAPM beta risk of corporate bonds as a whole of 0.2 to 0.3, which implies a risk premium of only 2.0%-2.5% per year, it seems disingenuous to rationalize the BBM-related annualized alpha spread of almost 4% as the outcome of an omitted risk control.

Papers by Daniel and Titman (2006) and Gerakos and Linnainmaa (2017) point out that a large portion of book-to-market's equity return predictability is linked to the ratio's correlation with long-term past returns and, accordingly, changes in firm size. Bali, Subrahmanyam, and Wen (2019) show that 3-year past returns (measured as the bond return from month $t-48$ to month $t-13$) are a corporate bond characteristic that strongly predicts return reversal. We omitted this control characteristic because requiring this 3-year past return limits sample size in both the time series and cross-sectional dimensions, i.e., it trims 48 months from the sample's beginning date and halves the size of the average cross-section. Nevertheless, in horse races between

[16] Our results are also not driven by outliers. Eliminating the observations that rely on the top 100 or bottom 100 bond prices has a negligible effect on our findings.

3-year past return and BBM, using the key specifications of Table 3 (plus the 3-year past return), the coefficient on the 3-year past return is never significant and economically small. For example, in specifications analogous to Table 3's specifications 5 and 7, the coefficients on the BBM Q5 dummy is 0.250 (t = 2.55) and 0.303 (t = 3.29), while those on the 3-year past return Q5 dummy are 0.006 (t = 0.08) and –0.016 (t = –0.20), respectively. While the sample used here, being shorter and with fewer bonds each month, prevents direct comparison with Table 3, it strongly suggests that BBM subsumes the 3-year past return effect as a predictor of corporate bond returns.

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 the BBW factor model (Panel A) and the Augmented BBW factor model (Panel B), respectively. The BBW 5-factor model has factors that control for overall bond market risk, credit risk, downside risk, liquidity risk, and short-term bond return reversal; the BBW Augmented 6-factor model adds a term structure factor. Compared to Table 3's FM cross-sectional analysis, Table 4's time series factor model regressions have the advantage of including bond observations that lack data on the controls. They also facilitate alpha analysis of each of the BBM quintile portfolios and the use of both equal and value weighting.

In particular, for BBM quintile portfolio q, we run Black, Jensen, and Scholes (1972) time series regressions of the quintile portfolio's returns (in excess of 1-month USD LIBOR), on five (Panel A) or six (Panel B) risk factors,

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

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

The first row of each of panel A's top half (EW portfolios) and bottom half (VW portfolios) shows that all of the quintile portfolios have positive risk-adjusted returns. For EW portfolios, this may in part be due to the fact that the BBW factors value-weight returns, while the returns that are risk-adjusted weight returns equally. This hypothesis is consistent with smaller VW than EW alphas for each of the five BBM quintiles. Moreover, as discussed in Section 2.2, the returns of the quintile portfolios may be upwardly biased due to noise in the beginning price for the return. We believe this bias is greater for Quintile 1 than for Quintile 5 because Quintile 5 bonds transact more frequently than Quintile 1 bonds. On average, the bonds in Quintile 5 trade 108 times in month $t + 1$ whereas those in Quintile 1 trade on average 42 times. This makes the statistically significant 19 bp per month Q5 – Q1 spread for EW portfolios (about 2.3% per year), as well as the statistically insignificant 12 bp per month spread for VW portfolios, conservative estimates of their true alpha spreads.

Table 4 Panel A's EW 19 bp alpha spread is smaller than the alpha spread from any of Table 3's odd-numbered (non-parametric) specifications, including the two lowest—Specifications 5 and 7 report alpha spreads of 27 and 32 bp per month, respectively. Part of the reason for the small EW alpha spreads in Table 4 Panel A's 5-factor model is the BBW model's factor risk selection. It controls for some sources of factor risk, like credit risk, which reduce the Q5 – Q1 spread. However, it lacks a factor control for the term structure of interest rates, even though bonds with long effective maturity tend to covary more with each other than with short maturity bonds and vice versa.

To control for factor risk arising from the term structure, Table 4 Panel B supplements the BBW factors with one additional factor. Accounting for the fact that both coupon and credit rating influence the effective maturity of a bond, we create a term structure factor in the spirit of BBW. To this end, we conduct independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We then take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. 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's FM regressions.

Because the excess returns are upwardly biased, we cannot easily ascertain if the spread is driven more by the long than the short end, or whether the profitability of a BBM strategy would be reduced by short-sale constraints.[17] However, if the bias was the same across all five quintile portfolios and the true alphas of the five EW quintile portfolios averaged to zero, each of the reported EW alphas in Panel A would be 22 bp per month higher than the corresponding true alpha. Reducing each alpha by the 22 bp bias would then generate a Q1 intercept of –0.02 and a Q5 intercept of 0.18. Under these assumptions, about 90% of the true alpha spread comes from the long end (Q5) and about 10% from the short end (Q1).

4 Understanding the BBM Alpha: Risk or Mispricing?

We now assess further evidence pertinent to the two competing explanations for BBM's success at predicting returns in Tables 3 and 4: first, that the BBM signal proxies for an omitted risk control; second, that extreme BBM quintiles contain mispriced bonds. This evidence includes the efficacy of the BBM signal when the signal is delayed, BBM's relative ability to predict the returns of the 20% most default-prone fixed income securities, and finally, the relatively small difference in the risk adjustment attached to common covariation among corporate bonds with small and large amounts of the BBM attribute.

4.1 Signal Delay

Figure 2 plots alpha spreads (coefficients on the BBM Q5 dummy in Specification 7 of Table 3) for signal delays ranging from zero to eleven months. In contrast to Table 3, which has BBM signals and returns beginning in January and February 2003, respectively, Figure 2's signals commence between January 2003 and December 2003, depending on the lag. Figure 2's returns always commence January 2004. Starting all return series at the same month, irrespective of the signal lag, facilitates apples-to-apples comparisons. The alpha spread is 30 bp per month with no delay, i.e., a first signal from December 2003. This value is similar to the 32 bp per month coefficient reported in Table 3, despite the shorter return series. Figure 2 also indicates that the alpha spread

[17] Asquith, Au, Covert, and Pathak (2013) show that the cost of shorting corporate bonds is comparable to that of stocks.

declines to about 9 bp per month when the signal is delayed by two months, losing about 70% of its efficacy. The spread meanders with further delay, ranging between 2 and 12 bp per months with a slow downward trend.

Figure 2's pattern is more consistent with the mispricing hypothesis. Bonds with extreme BBM ratios may ultimately end up with less extreme BBM ratios. However, BBM is an attribute that evolves slowly, and it requires large price changes to move a bond from one BBM quintile to another. Thus, most of the Q5 and Q1 quintile bonds remain Q5 and Q1 bonds for quite a few months and even years.[18] In contrast to Figure 2's rapid decay in signal efficacy, the slow evolution of the BBM attribute implies that stale BBM signals should predict bond returns if the predictability stems from BBM proxying for an omitted risk attribute.

To further articulate the argument against the risk explanation, recognize that the risk premium BBM would have to proxy for is a secondary risk attribute. It is therefore unlikely to be larger than 5% per annum, the premium of a primary risk attribute, calibrated as the return on a corporate bond index of senior unsecured bonds over the risk-free rate during this sample period. However, if BBM proxied for a premium that is even this large, virtually all bonds in Q5 compared to Q1 must carry this premium to account for the 5% annualized return spread observed. Generating a 4% annualized alpha spread after controls for known risk attributes would be even harder. However, even if this were the case, the departure rate and destination quintiles of bonds that start out in the two extreme quintiles cannot dissipate a BBM risk premium effect as rapidly as Figure 2 indicates it should. For example, after one month, about 14% of the bonds in the two extreme quintiles departed their quintiles, yet signal efficacy diminishes by 42%. At the two-month lag, alpha declines by 70%, but only about 16% of the bonds in Quintiles 1 and 5 depart for the three interior quintiles. Moreover, as time evolves, bonds that leave the extreme quintiles tend to move to adjacent quintiles, which have alphas and returns that are closer

[18] Because BBM is a stable trait with wide cross-sectional variation, it takes many months, if not years, to evolve into a substantially different value, just as Gerakos and Linnainmaa (2017) document for equity book-to-market. To verify the stability of our quintile portfolios, we compute the ratio of bonds that were in the quintile in month $t-1$ and leave for other quintiles in month t to the total number of bonds in the quintile in month $t-1$. The time-series average of the fraction of bonds leaving each quintile is 12%, 27%, 32%, 32%, 16% for Q1, Q2, Q3, Q4, and Q5, respectively. These values also suggest that the quintiles with the highest and lowest BBM tend to be more stable than those in the middle.

to those of their more extreme neighbors.[19]

By contrast, if the mispricing hypothesis explains BBM's effect on returns, delays in implementing the BBM signal could easily lead to Figure 2's pattern of rapid alpha decay. This is because mispricing is unlikely to be distributed evenly within extreme BBM quintiles and can be far larger than a monthly risk premium. A few highly mispriced bonds within those quintiles can explain Table 3's results even when the quintile's remaining bonds trade at prices much closer to fair value.[20] When the highly mispriced bonds experience convergence, which can occur rapidly once they are identified as mispriced, the BBM quintile will consist of bonds that are close to being fairly valued and the BBM signal becomes 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 bond 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 Default Risk and Signal Efficacy

Table 3's control for credit ratings and nearness to default help to dismiss claims that BBM's effect on returns are due to an omitted credit risk control. Simple calibrations reinforce this argument. In particular, the YTM difference between BBM Q5 and Q1 bonds is less than 13 bp per month (Table 2 Panel A), but this difference in promised returns has to exceed the spread in their risk-related expected returns: Compared to its YTM, the expected return of the more default-prone Q5 bonds is likely to shrink by a greater amount than the expected return of the Q1 bonds. However, the BBM return spread is 44 bp (Table 2 Panel B), about four times larger than the spread in the quintile pair's promised yields; even with all controls, the 32 bp spread in alpha (Table 3) is twice as large as the YTM spread.

[19] Indeed, the unreported coefficients on BBM quintiles 2–5 are monotonically increasing and significant in all of Table 3's odd-numbered specifications.

[20] Chordia et al. (2017) argue that most corporate bonds are more likely to be priced efficiently because institutional investors dominate in this market. Furthermore, as bonds have finite maturity, their market prices may converge to fair values more quickly than stock prices do.

Moreover, if BBM merely proxies for inadequate credit risk controls, the BBM anomaly should be stronger for bonds that are nearer to default. Table 5 adds interaction dummy variable regressors to Table 3's regressions. The interaction terms multiply each BBM quintile dummy by a dummy for the 20% of bonds that are nearest to default (Panel A) or the 20% with the lowest credit rating (Panel B). The coefficient on the interaction dummy measures whether the BBM alpha spread between BBM Q5 bonds and BBM Q1 bonds is larger for bonds ranked among the top 20% in default risk. For brevity, Table 5 only reports coefficients on the BBM Q5 dummy and the interaction between the BBM Q5 dummy and the default-related dummies.

In all of Table 5's specifications, the coefficient on the BBM Q5 dummy is significant, indicating that the BBM anomaly remains for the 80% of bonds least likely to default, while the coefficient on the interaction dummy is insignificant. For example, in Specification 7 of Panel A, the bonds issued by firms nearer to default have a 10 bp per month lower alpha spread than the bonds that are further from default. All interactions terms in the 16 specifications of Panels A and B are statistically insignificant. These results support our claim that mispricing, rather an omitted risk control, drives our result. Next, we study whether an omitted risk control tied to the riskless term structure might explain our findings.

4.3 BBM and Lower Risk Treasury Notes and Bonds

BBM may also be a risk proxy because it better captures duration or related interest rate risk measures that are common to all bonds. However, if this is the case, Treasury securities should exhibit a BBM anomaly. Table 6 repeats Table 3 using U.S. Treasury notes and bonds instead of corporate bonds.[21] Panel A covers the period from July 1961 to December 2019; Panel B covers the period prior to the period we study with TRACE; finally, Panel C studies the return period over which we study corporate bond pricing with TRACE—February 2003 to December 2019. The coefficient on the BBM Q5 dummy is insignificant for all specifications and all time periods. By contrast, YTM is a significant predictor of U.S. Treasury returns. This finding is consistent with our controls for duration and term risk being adequate, leaving other risks or, more likely, mispricing as the

[21] We use the CRSP U.S. Treasury Database, excluding T-bills, TIPS and Treasuries with special tax provisions. Also, control variables that cannot be applied to Treasuries are necessarily excluded.

better explanation for the BBM anomaly in the corporate bond market.

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

Table 6 Panel D reports the average values for Table 6 Panel C's regression coefficients across 1,000 Monte Carlo simulations. Panel D's results are virtually identical to those in Panel C. For example, with Specification 5, Panel D's coefficient on BBM is an insignificant 0.039, whereas in Panel C, the corresponding coefficient is –0.014. The similarity of Panel C and D validates the martingale procedure as an appropriate methodology to assess the BBM anomaly in the face of thin trading. In work not reported in a table, we repeated Table 6 Panel D but randomly perturbed the Treasury prices on the 3 days by a randomly assigned positive or negative 20 basis points, each with equal probability. This procedure mimics the impact of a 20 bp half bid ask spread. Results with the randomly perturbed prices were highly similar.

4.4 Does BBM Factor Risk Explain the BBM Alpha?

According to Davis, Fama and French (2000), models that use the sensitivity to the high-minus-low equity book-to-market ratio (HML) factor as a risk proxy explain the equity book-to-market anomaly as well as the book-to-market attribute itself. They use this to argue that equity book-to-market is driven by risk. Here, we construct a bond market version of HML and show that it has only modest ability to diminish the BBM effect.

To create an HML-like factor, we parrot Fama and French's (1993) procedure. Each month, we divide bonds into one of six categories based on two bond size categories (market value outstanding) and three BBM categories. Within each of the two bond size categories (large and small), we compute each month's return spread between a value weighting (with weights proportional to each bond's market capitalization) of the top- and bottom-third BBM bonds. Averaging the "large" and "small" bond return spreads generates that month's Bond HML factor (BHML).

Table 7 repeats Table 4's time series factor model regressions, adding BHML factor returns. The top half of Table 7 corresponds to Table 4 Panel A (the BBW factor model) and the bottom half corresponds to Table 4 Panel B (the Augmented BBW factor model). For brevity, Table 7 only reports intercepts (alpha) and factor betas on the additional factors. The table's rightmost column indicates significant Q5 – Q1 beta spreads on the BHML factor with both factor models. The rightmost column and first row also displays a significant alpha spread of 15 bp per month (t = 3.11)— a nearly 25% reduction from Table 4 Panel A's 19 bp per month spread. Including the term structure factor yields a similar, significant alpha spread (14 bp, t = 3.17). The reduction in alpha from Table 4 is not entirely surprising. If we had constructed the BHML factor as an equal-weighting of the top and bottom BBM quintile returns, mathematics would ensure a zero-alpha spread. The modestly differing design of BHML similarly leads to a downward bias in the alpha spreads, albeit a less dramatic one. Such a bias makes the significance of the Q5 – Q1 intercepts, even at 14 to 15 bp per month, quite telling. It suggests that it would be conservative to argue that factor risk does not fully explain the BBM anomaly.

5 Alternative Signals, Junior Bonds, Trading Frequency, and Transaction Costs

The previous section argued that mispricing rather than an omitted risk control best explains BBM's ability to predict bond returns. This section analyzes whether BBM's return-predictive ability survives competition with a related mispricing metric, generalizes to a sample that includes junior bonds, and could possibly be generated by off-market prices. It also addresses whether a BBM strategy can be implemented in a cost-effective manner.

5.1 An Alternative Signal Rooted in Mispricing

We first study whether the BBM signal is simply a crude representation of a mispricing anomaly discovered by BG (2018) for equities. The BG signal, described in Section 2.3, can be viewed as a sophisticated BBM signal. In lieu of a single accounting construct, book debt, the BG signal uses predictions from the 28 most commonly reported accounting variables to scale a bond's price. BG (2018) refer to the scaling as a "fair value," obtained as the cross-sectional OLS regression prediction from a set of accounting items. Thus, the BG signal's fair value is simply month t's market-wide norm for the linear function of 28 accounting variables that best explains the aggregate market values of firms' bonds. Sorting on the percentage price deviation from the linear prediction is identical to a firm-level sort of the price to fair value ratio. Within each firm, we assign the same BG mispricing percentage to each of its bond.

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

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

5.2 BBM's Return-Predictive Ability for All Bonds

Up to this point, our tests include only senior unsecured bonds with no embedded options other than call provisions. As noted earlier, this is the group of bonds that researchers traditionally study, as risk controls for this subsample of TRACE are well established. As a robustness check, Table 9 repeats Table 3 and 4's methodologies, but for all TRACE bonds, including junior bonds and bonds with put options attached to them. For brevity, Table 9 Panel A, which parrots Table 3's FM regressions on the larger bond sample, reports coefficients only for selected regressors of interest. Panel B repeats Table 4's factor model regressions, reporting only the intercept for EW quintile portfolios for brevity. Panel C repeats Table 7's factor model regression for EW quintile portfolio, reporting only intercepts and factor betas on the BHML factor for brevity.

The bonds Table 9 uses to supplement the original sample generally trade less frequently and are riskier than the original sample's senior unsecured bonds. With a full set of controls (Specifications 7 and 8), Table 9 Panel A's results are stronger than those in Table 3. For example, the coefficient on the BBM Q5 dummy variable in Specification 7 of Panel A is 38 bp per month (t = 4.26)—representing an alpha of almost 5% per year. By contrast, the corresponding coefficient from Table 3 Specification 7 is 32 bp per month (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 restricted sample's factor models, as outlined in Tables 4 and 7, respectively. Thus, the BBM anomaly is stronger for the all-bond sample.

5.3 Off-Market Prices

One alternative explanation for our results is that the prices used to compute returns are available only to some investors rather than being fair estimates of mid-market prices. We dismissed this issue previously with Table 2 Panel C's summary statistics, showing that, if anything BBM quintile 5's returns are relatively more likely to be initiated at ask than bid prices.[22] The reverse is true for quintile 1, implying that the reported Q5 – Q1 spreads, if anything, understate the spread in mid-market prices.

[22] The Q5 – Q1 return and alpha spread is negative if we use only ask prices (dealer sells to customer) in Q5 for the beginning return price and bid prices (dealer buys from customer) for Q1. This implies that transaction costs outweigh the documented alpha spread, a topic studied in more depth later.

If the relative proportion of bids and asks had been the same for BBM quintiles 1 and 5, off-market charges for liquidity (e.g., if favored customers exist) might contaminate returns. In this case, if bid prices tend to be at relatively tighter spreads in quintile 1 (compared to quintile 5) and ask prices at relatively tighter spreads in quintile 5, we would observe higher returns in quintile 5 than in quintile 1. In light of Table 2 Panel C's evidence, spurious generation of the BBM anomaly could only occur if this quintile-specific bid-ask asymmetry in off-market liquidity charges overcame the greater preponderance of ask transactions initiating quintile 5 returns. If this happened, however, and explained our findings, customer transactions that initiate returns in quintiles 1 and 5 would generate higher BBM alpha spreads than dealer-to-dealer transactions.

Table 10 investigates this issue using Table 3's FM regression methodology. It adds interaction terms to the BBM quintile dummies for a return-beginning price that comes from a customer transaction. The first column's 0.328 coefficient on BBM Quintile 5 now represents the Q5 – Q1 alpha spread of dealer-to-dealer transactions. The interaction term with the customer beginning price dummy is insignificant in both specifications, indicating that customer transactions have about the same alpha spread as beginning price transactions between two dealers. The table thus indicates that dealer-only beginning price transactions have a similar Q5 – Q1 alpha spread as seen earlier in Table 3. Clearly, asymmetries in the costs dealers charge to buying vs. selling customers across the quintiles does not explain BBM's return effect.

5.4 Buy-and-Hold Returns

Pension funds and other institutional investors may buy and hold bonds without rebalancing their portfolios frequently. Less frequent trading reduces the strategy's transaction costs, a topic we study shortly. To address the issue of statistical inference from 12-month returns that roll over each month, we apply the technique of Jegadeesh and Titman (1993).[23] Table 11 reports the factor model alphas (computed as in Table 4) of the five

[23] Their method constructs an independent monthly return series that closely mimics the buy-and-hold outcome. To compute the return to a twelve-month buy-and-hold BBM quintile, we take the average of twelve (equal-weighted) partially overlapping strategies that are simultaneously implemented each month. Each of the twelve strategies is based on a BBM quintile indicator that has one of the months 0–11 as lags for signal delay. This yields a single series of monthly returns that, except for minor effects from endpoint months and compounding, aggregate to the buy-and-hold returns of the quintile portfolio. Differencing the buy-and-hold monthly returns of quintiles 5 and 1, then averaging, yields the alpha spread for the buy-and-hold BBM strategy.

buy-and-hold BBM quintiles and the long-short BBM strategy. The alpha spread between the Q5 and Q1 portfolios is 12 bp (t = 2.05) and 16 bp (t = 2.67) per month for the BBW factor model and the augmented BBW factor model, respectively. The alpha difference suggests that profits to the BBM strategy are approximately halved, making the strategy less attractive, when rebalancing annually as opposed to monthly.

5.5 Transaction Costs

BBM's extreme quintile alpha spread before accounting for transaction costs is a useful metric for assessing bond market efficiency. However, deviations of bond prices from their fair values do not represent profit opportunities for market participants if transaction costs exceed gross profits (BG, 2021). The corporate bond market is known to be illiquid, and transaction costs are generally high (Chen, Lesmond, and Wei, 2007; Edwards, Harris, and Piwowar, 2007; Bao, Pan, and Wang, 2011; Feldhütter, 2012). Therefore, the alphas arising from the BBM signal may not be exploitable by arbitragers as a stand-alone trading strategy.

Our methodology applies the martingale property of asset prices to estimate end-of-month hypothetical transaction prices. These hypothetical transactions would incur transaction costs in the form of a half-spread between the transaction price and a "mid-market" price at which the transaction would take place if transaction costs were zero. Assuming a transaction cost that is symmetric for buys and sells, we can measure the effective half spread by halving the effective full spread computed from actual transactions.

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

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

In particular, for month t's return, we denote the weight difference as $\mathbf{w}_{q,t+1} - \mathbf{D}_t \mathbf{w}_{q,t}$, where $\mathbf{D}_t$ is an $N \times N$ diagonal matrix, with the j-th diagonal element being the month t gross return $(1 + R_{j,t})$ of bond j divided by the month t gross return of BBM quintile portfolio q. $\mathbf{w}_{q,t}$ is an N-vector with each element corresponding to the vector of portfolio weights for quintile q in month t. This weight reflects each bond's (out of the N bonds in our sample) month t (zero or positive but equal) weight assigned by the end of month $t - 1$ signal. The beginning-of-month weights change over the course of the month as a result of the bond return $R_{j,t}$—hence the scaling by $\mathbf{D}_t$.[24] Each element of month t's difference vector is assigned one of five half-spreads tied to the quintile the bond belongs to throughout month t. If the j-th element of $\mathbf{w}_{q,t+1}$ is positive, bond j is assigned month t's effective half spread for bonds in quintile q. Algebraically, month t's transaction cost per dollar for updating quintile q's portfolio at the end of month t is

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

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

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

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

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

Table 12 reports average portfolio turnover and transaction costs as well as gross and net performance for trades restricted to the lowest and highest BBM quintiles. The alpha column reproduces the factor model alphas in Panel A for monthly rebalancing (from Table 4) and in Panel B for a one-year buy-and-hold strategy (from Table 11). With monthly rebalancing, the long-short BBM strategy has a pre-transaction cost (i.e., gross) BBW factor model alpha of 19 bp per month. The transaction costs associated with its turnover of 31% amounts to 50 bp for all investors, which exceed the alpha spreads computed for the strategy. Even applying the (more than 50%) lower transaction costs of 19 bp for large transactions to the same gross alpha offers no consolation, yielding an insignificant 2 bp per month net alpha.[25] Augmented BBW factor model alphas net of transactions costs are an insignificant 7 bp per month for large transactions.

Buy-and-hold strategies are designed to reduce turnover, which is borne out in Panel B with turnover of 7% and transactions costs of 11 bp and 4 bp for all investors and institutional investors, respectively. While these strategies also result in lower risk-adjusted profits due to alpha decay, all buy-and-hold alphas net of transactions costs are positive. While net profits are still too low for all investors to exhibit significance, the Augmented BBW model yields significant net profits of 12 bp per month (t = 2.06). Thus, the buy-and-hold variation of the strategy does survive the transaction costs incurred by larger 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.

6 Conclusion

This paper studied BBM's role in the pricing of corporate bonds. The alpha difference between extreme BBM quintile portfolios—32 bp per month with the most extensive controls—is sizable considering the volatility of corporate bond returns compared to stock returns. The paper presented evidence that the BBM trading strategy's alpha is unlikely to stem from an omitted risk control. For one, it is difficult to conceive of omitted risk controls with sufficient risk premia when cross-sectional FM regressions already control for most of the return-related bond and equity characteristics studied in the literature. Moreover, time series factor model regressions with six risk factors confirm a significant alpha. Alpha spreads are of larger economic magnitude when the sample includes junior bonds and bonds with exotic options.

This leaves mispricing as the best explanation for the BBM anomaly. That explanation is reinforced by the pattern of profits earned when the BBM signal is delayed, calibrations from yield spreads, similar BBM signal efficacy for bonds with more default risk, and the inability of factor betas to explain BBM profits, even with an additional HML-like factor for bonds. Moreover, the term structure of riskless interest rates cannot

[25] Factor model net performance is the intercept from regressing quintile portfolio excess returns net of monthly transaction costs on factors. Subtracting transaction costs monthly alters factor betas, implying that Table 12's net performance does not exactly equal the difference between Table 4 and 11's average (gross) alpha and average transaction costs.

explain the BBM anomaly, as the BBM signal does not predict U.S. Treasury returns. The latter is true even when artificially forcing transactions in Treasuries to mimic the sparse data structure of corporate bonds.

In both reported and unreported analyses, we contemplated the possibility that the illiquidity of bonds could account for our findings. Reported results suggest that the Jensen's inequality bias in returns makes the reported magnitude of the BBM alpha spread conservative. BBM Q1 portfolio bonds trade less frequently than the BBM Q5 bonds. Thus, if bond returns are upwardly biased due to Jensen's inequality, they are more upwardly biased for the short leg (Q1) than the long leg (Q5) of the BBM strategy. We also find that there are more ask than bid transaction initiating our long positions, and more bid transactions initiating our short positions. Finally, our results are not driven by customers receiving off-market deals or a correlation between BBM and the proportion of bids and asks. The results are also insensitive to market microstructure controls.

We emphasize that our reported results are conservative. Most of our focus is on senior unsecured bonds with, at best, simple call options (usually of the make-whole variety for which exercise offers little economic advantage). When we analyze a larger set of TRACE bonds that includes junior bonds, our alphas are considerably larger. We also do not allow a month's signal to be implemented if it first becomes publicly known in the last seven days of the month. Finally, we only compute returns from intra-month prices and eschew "end-of-month" WRDS bond returns for this reason. The latter procedures lengthen the time between signal and implementation by an average of about half a month. It also means that the unscaled positive alpha spreads we report are for periods of less than a month and would be larger if they were rescaled to cover a full month.

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

The BBM anomaly's mispricing explanation may explain the book-to-market effects for other asset classes. If bonds, which have adequate risk controls, favor the mispricing explanation for BBM's effect, we need to take mispricing more seriously in other asset classes, like equity, where risk controls are harder to come by. Consistent with the equity mispricing explanation is the decline in equity HML since 2002 as trading frictions in equities declined and the equity book-to-market anomaly became more widely known in hedge fund circles.

Bond book-to-market ratios are highly negatively correlated with bond prices. While quintile sorts on bond prices also predict returns, we presented evidence that BBM is a better return predictor. The differences are not striking, however, and it would be acceptable to believe that the difference between a bond price anomaly and a bond book-to-market anomaly is semantic. For equities, this is largely the case as well. It is just that an equity share is an arbitrary way to scale a price, making equity book-to-market a less noisy mispricing metric than the share price. This, of course, 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,[26] including book-to-market, we see no reason to doubt that they are all part of the same phenomenon.

Alas, sentiment about a role for sentiment in asset pricing is controversial. This controversy is puzzling for researchers who long for a synthesis between two competing views of asset pricing. We do not believe that our results should be the source of any controversy. At one level, it is possible to say that at best, about 40% of bond prices deviate from their fair values by an average of no more than 0.75%.[27] For a bond with 10-year modified duration, this corresponds to a yield deviation from fair value of at most 8 bp. Markets may not be perfectly efficient, but it would be petty to dismiss efficient markets entirely for such a small sum.

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[26] See, for example, Fritzemeier (1936), Bachrach and Galai (1979), Basu (1978), Dubofsky and French (1988), and Lamont (1998).

[27] In Table 11, the annualized buy-and-hold return is 1.5%, which implies that the average bond in Q1 and Q5 is mispriced by 0.75%.

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

The figure shows the bond prices used to construct the signal and 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.

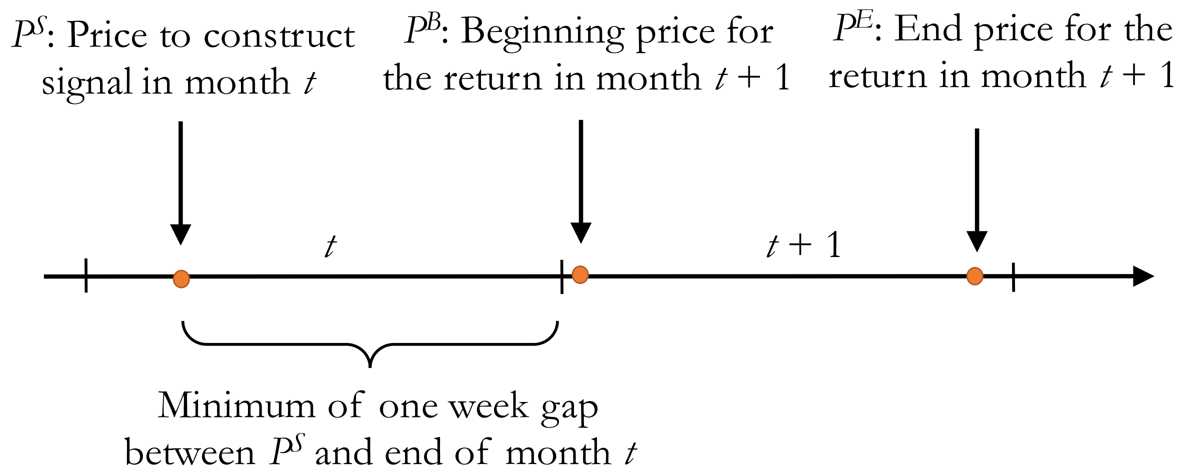


Figure 2: Signal Delay

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). Returns are regressed against the book-to-market quintile dummies lagged by one to twelve months. Control variables include bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The table employs quintile dummies for 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. Each month's quintiles are determined from sorts of firms with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. The return sample period is January 2004 to September 2020. All variables are defined in Appendix A.

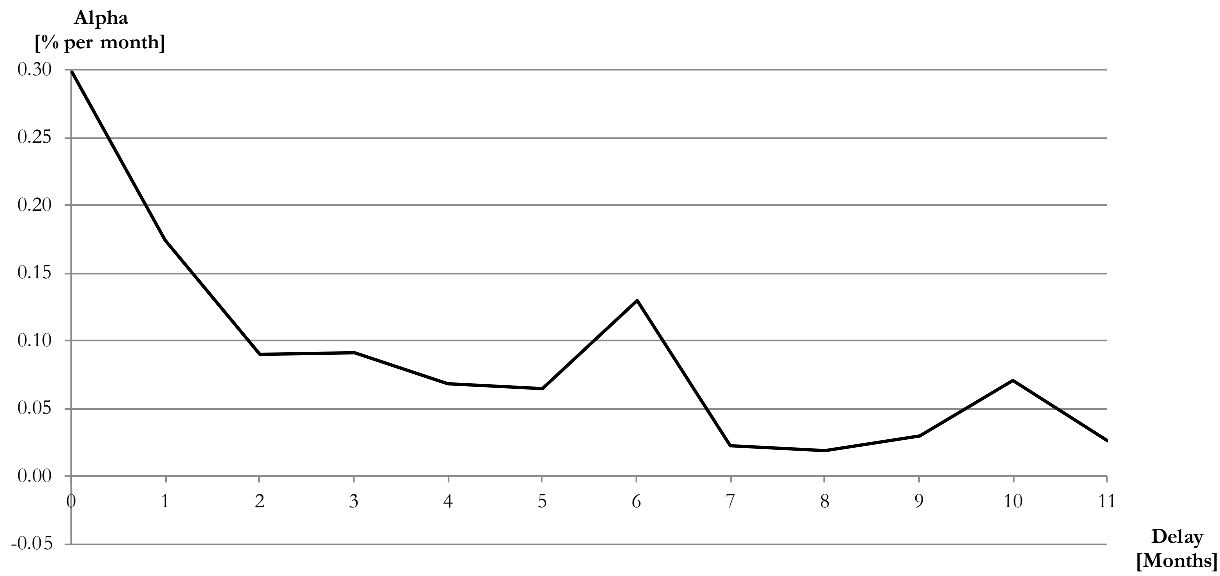
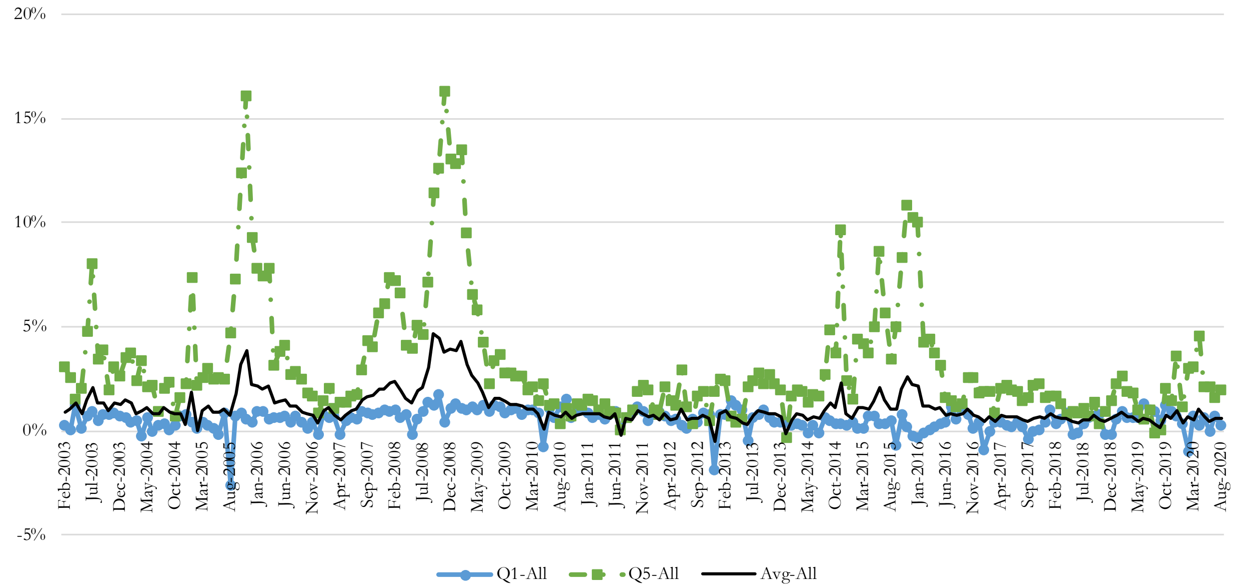


Figure 3: Monthly Bid-Ask Spreads for Bond Book-to-Market Quintiles

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 five quintiles.

Panel A: All Transactions



Panel B: Institutional Transactions

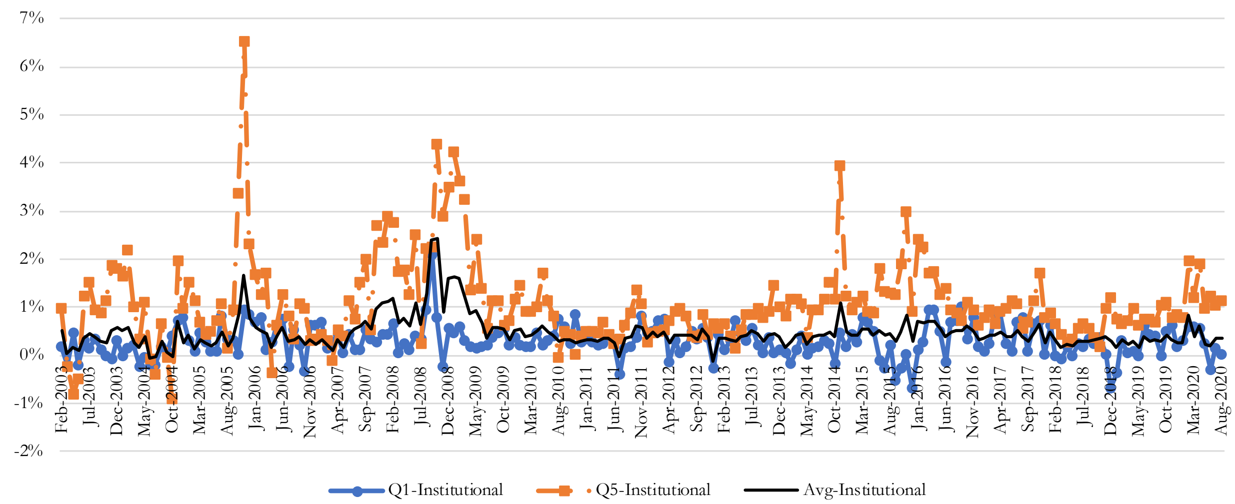


Table 1: Summary Statistics

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

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	459,040	15.9	8.0	8.0	8.0	9.0	11.0	14.0	26.0	37.0	89.0
All Bonds	566,346	19.4	8.0	8.0	8.0	9.0	11.0	18.0	34.0	52.0	134.0

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 (Panel B), and statistics on beginning prices for returns (Panel C). Panel A reports averages of various characteristics of bonds and issuing firms, including the time series average of the monthly mean characteristics across all observations ("All"), the average monthly cross-sectional correlation of the characteristic with BBM ("Correlation"), and the average of the monthly mean characteristics across quintiles of bonds sorted by bond book-to-market from Q1 (lowest) to Q5 (highest). Panel B reports equal- and value-weighted average returns on these portfolios, as well as the returns on the hedge portfolios with a long position in Q5 and a short position in Q1. Panel C reports the fraction of beginning prices for returns at bids, asks, and from dealer-to-dealer transactions by BBM quintiles. The sample consists of nonfinancial firms with U.S. dollar-denominated, senior unsecured corporate bonds without embedded options other than call options. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

Panel A: Bond and Firm Characteristics

			Bond Book/Market (BBM) Quintiles				
	All	Correlation	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)
Bond Book/Market	0.963	1.00	0.845	0.923	0.961	0.994	1.094
Bond Mispricing	-0.001	0.29	-0.011	-0.005	-0.001	0.003	0.011
Bond Coupon Rate	5.513	-0.30	6.818	5.866	5.321	4.744	4.816
Bond Yield	4.779	0.42	4.682	4.218	4.341	4.469	6.191
Bond Credit Spread	1.579	0.35	1.466	1.300	1.325	1.230	2.571
Bond Value	532.2	-0.10	610.7	564.3	522.3	508.4	455.2
Bond Face Value	501.7	-0.03	508.0	517.5	500.2	503.2	479.8
Bond Age	4.870	-0.16	7.268	5.083	4.373	3.702	3.926
Bond Maturity	11.18	-0.10	16.41	10.184	8.832	8.445	12.02
Bond Duration	6.984	-0.14	9.388	6.666	5.924	5.688	7.248
Bond Rating	8.159	0.24	7.462	7.901	8.144	8.173	9.126
Bond Reversal	0.685	-0.05	0.814	0.706	0.665	0.639	0.662
Bond Momentum	3.421	-0.22	4.548	3.752	3.354	2.935	2.871
Bond Bid/Ask Spread	0.495	0.19	0.470	0.436	0.447	0.469	0.682
Number of Bonds	37.90	0.00	37.83	30.81	32.75	39.84	48.30
Number of Days from Beginning of Month	2.907	-0.08	3.899	2.843	2.602	2.587	2.741
Number of Days from End of Month	2.743	-0.08	3.727	2.714	2.478	2.413	2.508
Nearness to Default	-9.488	0.17	-10.10	-9.77	-9.479	-9.490	-8.605
Investment Grade	0.863	-0.24	0.954	0.910	0.869	0.854	0.726
Non-Investment Grade	0.137	0.24	0.046	0.090	0.131	0.146	0.274
Offering Price	99.49	0.05	99.23	99.49	99.55	99.61	99.56
Equity Mispricing	0.080	0.00	0.049	0.074	0.088	0.080	0.129
Equity Market Capitalization	42,720	-0.06	48,318	39,548	40,351	45,811	39,560
Equity Book/Market	0.652	0.20	0.591	0.601	0.604	0.640	0.825
Equity Beta	0.979	0.16	0.891	0.925	0.963	0.987	1.127
SUE	-0.003	-0.10	0.001	0.001	0.000	0.000	-0.016
Gross Profitability	0.226	-0.04	0.230	0.232	0.231	0.228	0.212
Earnings Yield	0.012	-0.28	0.056	0.053	0.047	0.038	-0.134
Equity Short-term Reversal	1.028	-0.03	1.067	1.061	1.051	1.053	0.910
Equity Momentum	10.59	-0.14	13.27	12.22	11.73	10.46	5.269
Equity Long-term Reversal	54.19	-0.10	58.54	58.03	56.28	54.01	44.13
Accruals	0.098	-0.03	0.093	0.105	0.112	0.107	0.077

(continued)

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

Panel B: Portfolio Returns

			Bond Book/Market (BBM) Quintiles					Q5-Q1 (high BBM - low BBM)			
	All	Correlation	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)	Fraction > 0	*p-value*	Average	*t-stat*
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]

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

	Bond Book/Market (BBM) Quintiles				
	Q1 (low BBM)	Q2	Q3	Q4	Q5 (high BBM)
Beginning Price of Bond Return in t + 1 at Bid	39.8%	39.6%	38.7%	37.6%	35.2%
Beginning Price of Bond Return in t + 1 at Ask	25.5%	24.8%	25.7%	27.2%	28.4%
Beginning Price of Bond Return in t + 1 from Dealer-to-Dealer Transaction	34.7%	35.6%	35.6%	35.3%	36.4%

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. Across different specifications, returns are regressed against end-of-prior-month values for bond book-to-market, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The table 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 firms with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for Quintiles 2, 3, 4, and 5 of each characteristic, but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. 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. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

(continued)

Table 3: Fama-MacBeth Cross-Sectional Regressions (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 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	

Table 4: Factor Model Time Series Regressions

The table shows results from time series regressions of monthly portfolio returns (in excess of 1-month USD LIBOR) on bond factor models. Bonds are sorted each month into quintiles based on bond book-to-market (BBM) and combined into equal-weighted or value-weighted portfolios. The table reports intercepts, slope coefficients, *t*-statistics, the number of observations, and R-squared separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the return spreads between the highest bond book-to-market (Q5) and lowest bond book-to-market (Q1) quintiles. Regressors for the BBW (2019) factor model in Panel A are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model in Panel B further adds a term structure factor. Standard errors are estimated using the Newey West (1987) procedure. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

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 Rating 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 Value at Risk 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	

Table 5: Default Risk

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics with interaction variables for bonds with high default risk. Across different specifications, returns are regressed against end-of-prior-month values for bond book-to-market, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The table 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 firms with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for Quintiles 2, 3, 4, and 5 of each characteristic, but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. All regressions include the fifth quintile dummy for nearness to default (Panel A) or for bond credit rating (Panel B), as well as interactions of these indicator variables with the fifth quintile dummy for bond book-to-market and the normal score of bond book-to-market, respectively. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. The table shows average coefficients and test statistics as well as the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

	(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
Panel A: 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	
Panel B: 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	

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 Treasury securities that are used to form BBM quintiles in each 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 5: Treasury Bonds (continued)

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

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

The table shows results from time series regressions of monthly portfolio returns (in excess of 1-month USD LIBOR) on bond factor models augmented with a high-minus-low factor based on bond book-to-market (BHML). Bonds are sorted each month into quintiles based on bond book-to-market and combined into equal-weighted portfolios. The table reports intercepts, slope coefficients, *t*-statistics, the number of observations, and R-squared separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the corresponding times-series of return spreads between the highest book-to-market (Q5) and lowest book-to-market (Q1) bond quintiles. To form the Bond HML factor, each month, we divide bonds into one of 6 categories based on bond size (aggregate market value outstanding) and bond book-to-market. For the 3 categories in the larger of the two bond sizes (bottom, middle, and top third of month-*t* bond book-to-market), we compute the spread in the month $t + 1$ value-weighted bond returns (based on bond market capitalization) between the top and bottom third bond book-to-market bonds. We then repeat the exercise for the firm in the smaller of the two bond sizes. We then average the two value-weighted return spreads and include the average as the Bond HML factor. Regressors for the BBW (2019) factor model are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model further adds a term structure factor. Standard errors are estimated using the Newey West (1987) procedure. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

	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: Bond Mispricing and Bond Book-to-Market

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics, including bond book-to-market and bond mispricing. Across different specifications, returns are regressed against end-of-prior-month values for bond book-to-market, bond mispricing, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The table employs quintile dummies for the characteristics as regressors. Each month's quintiles are determined from sorts of firms with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for Quintiles 2, 3, 4, and 5 of each characteristic but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) on bond book-to-market and bond mispricing for brevity. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. The table shows average coefficients and test statistics as well as the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

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

Table 9: Sample of All Corporate Bonds

The table shows results for regressions using the sample of all bonds including junior bonds and bonds with embedded options. Panel A shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics for the same regression specifications as in Table 3. Across different specifications, returns are regressed against end-of-prior-month values for bond book-to-market, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The panel 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 firms with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for Quintiles 2, 3, 4, and 5 of each characteristic, but the 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. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. The 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 portfolio returns (in excess of 1-month USD LIBOR) on bond factor models. Bonds are sorted each month into quintiles based on bond book-to-market (BBM) and combined into equal-weighted portfolios. 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. Regressors for the BBW factor model are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model further adds a term structure factor. Standard errors are estimated using the Newey West (1987) procedure. 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 portfolio returns (in excess of 1-month USD LIBOR) on a risk model augmented with a high-minus-low factor based on bond book-to-market (BHML). Bonds are sorted each month into quintiles based on bond book-to-market (BBM) and combined into equal-weighted portfolios. 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. To form the Bond HML factor, each month, we divide bonds into one of 6 categories based on bond size (aggregate market value outstanding) and bond book-to-market. For the 3 categories in the larger of the two bond sizes (bottom, middle, and top third of month-t bond book-to-market), we compute the spread in the month $t+1$ value-weighted bond returns (based on bond market capitalization) between the top and bottom third bond book-to-market bonds. We then repeat the exercise for the firm in the smaller of the two bond sizes. We then average the two value-weighted return spreads and include the average as the Bond HML factor. Regressors for the BBW (2019) factor model are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model further adds a term structure factor. Standard errors are estimated using the Newey West (1987) procedure. For brevity, the panel only displays coefficients and t-statistics for the regression intercept and the Bond HML factors 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. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

(continued)

Table 9: Sample of All Corporate Bonds (continued)

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	

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	

(continued)

Table 9: Sample of All Corporate Bonds (continued)

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

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

Table 10: Off-Market Prices

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics. BBM quintile dummies have interaction variables for dealer-customer bond transactions with the omitted dummy reflecting a dealer-to-dealer transaction. Across different specifications, bond returns are regressed against end-of-prior-month values for bond book-to-market, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The table employs quintile dummies for the characteristics as regressors except for bond book-to-market in specification (2), which employ the normal score of bond book-to-market. Each month's quintiles are determined from sorts of firms with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. 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. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. The table shows average coefficients and test statistics 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. The return sample period is February 2003 to September 2020. All variables are defined in Appendix A.

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

Table 11: Buy-and-Hold Returns

The table shows results from time series regressions of monthly bond portfolio returns (in excess of 1-month USD LIBOR) on risk factors. Following Jegadeesh and Titman (1993, 2001), the table measures the monthly performance of a portfolio held for 12 months with the following non-overlapping returns methodology: Bonds are sorted each month into 12 sets of quintiles based on bond book-to-market (BBM) that is delayed from 0 to 11 months and combined into equal-weighted portfolios within the same signal delay cohort. The monthly return that is used in the regression equally weights the twelve portfolios that belong to the same quintile. The table reports intercepts and associated *t*-statistics separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the corresponding times-series of return spreads between the highest book-to-market (Q5) and lowest book-to-market (Q1) bond quintiles. Regressors for the BBW (2019) factor model are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model further adds a term structure factor. Standard errors are estimated using the Newey West (1987) procedure. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The return sample period is January 2004 to September 2020. All variables are defined in Appendix A.

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

Table 12: Turnover and Transaction Costs

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

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

Appendix A: Variable Definitions

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

Variable	Definition	Source
Bond Variables		
Bond Book/Market	Face value of a bond divided its market value	TRACE, Mergent FISD
Bond Mispricing	-1 * Residual/ Market Value of Total Liabilities of firm	
Bond Yield	Yield to maturity (%)	TRACE, Mergent FISD
Bond Credit Spread	Difference between yield of bond and swap rates with matched cash flows	TRACE, Bloomberg
Bond Value	Market value of bond	TRACE, Mergent FISD
Bond Face Value	Face value of bond	Mergent FISD
Bond Age	Years elapsed since issuance	Mergent FISD
Bond Maturity	Remaining time to maturity (in years)	Mergent FISD
Bond Duration	Macaulay duration of bond (in years)	TRACE, Mergent FISD
Bond Coupon Rate	Coupon rate of bond (%)	Mergent FISD
Bond Bid/Ask Spread	Bid/Ask spread of bond. Daily spreads are computed as the difference between average dealer sells and average dealer buys, scaled by the average of buys and sells in the day. We use dealer-to-customer trades only. Monthly spread is the average of daily spreads in month t.	TRACE
Bond Reversal	Returns of bond in month t	TRACE, Mergent FISD
Bond Momentum	Six-month returns over month $t-6$ to $t-1$, computed using the beginning of the month price in $t-6$ and the end of the month price in $t-1$.	TRACE, Mergent FISD
Bond Rating	Rating of bond expressed in numerical values from AAA (1) to D (22). Credit rating is from S&P when available, and from Moody's when S&P's rating is not available.	Mergent FISD
Number of Bonds t+1	Number of outstanding bonds of firm in calendar month $t+1$	Mergent FISD
Percent of Bond Market Capitalization Traded in t+1	Percentage of the market values of bonds of a firm that trade in calendar month $t+1$ as a fraction of the market value of bonds with signals in month t	Mergent FISD
Number of Days from Beginning of Month t+1	Difference in calendar days between the date of first transaction in month $t+1$ and the first trading date of month $t+1$.	TRACE
Number of Days from End of Month t+1	Difference in calendar days (in absolute values) between the last trading date of month $t+1$ and the date for month $t+1$ end-of-month transaction.	TRACE
Investment Grade	Dummy variable which equals one if bond's credit rating is BBB- or above.	Mergent FISD
Non-Investment Grade	Dummy variable which equals one if bond's credit rating is BB+ or below.	Mergent FISD
Offering Price	Price at which bond is initially sold to investors.	Mergent FISD
Bond Market Factors		
Bond Market Factor	Excess return on the value-weighted corporate bond market portfolio.	TRACE, Mergent FISD
Bond Value at Risk Factor	Return difference between bonds with low value-at-risk (as measured by the second worst return in the previous three years) and bonds with high value-at risk. Bonds are independently sorted into 25 value-weighted portfolios based on credit rating and value-at-risk, and the factor is formed as the average across rating quintiles.	TRACE, Mergent FISD
Bond Rating Factor	Return difference between bonds with high default risk (as measured by credit rating) and bonds with low default risk. For each of the double-sorts on value-at-risk, illiquidity and reversal, a rating factor is formed by taking the average across the non-rating characteristics. The rating factor is the average of the three factors.	TRACE, Mergent FISD
Bond Illiquidity Factor	Return difference between bonds with high illiquidity (the Roll measure) and bonds with low illiquidity. Bonds are independently sorted into 25 value-weighted portfolios based on credit rating and illiquidity, and the factor is formed as the average across rating quintiles.	TRACE, Mergent FISD
Bond Reversal Factor	Return difference between bonds with low reversal (the past one-month bond return) and bonds with high reversal. Bonds are independently sorted into 25 value-weighted portfolios based on credit rating and reversal, and the factor is formed as the average across rating quintiles.	TRACE, Mergent FISD
Bond Term Structure Factor	Return difference between bonds with long time-to-maturity and bonds with short time-to-maturity. Bonds are independently sorted into 125 value-weighted portfolios based on credit rating, coupon rate and maturity, and the factor is formed as the average across rating and coupon rate quintiles.	TRACE, Mergent FISD

(continued)

Appendix A: Variable Definitions (continued)

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