Book-to-Market, Mispricing, and the Cross-Section of Corporate Bond Returns

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Abstract

A corporate bond's book value divided by its market price strongly predicts its return from actual transactions occurring at least eight days after observing the signal. Bonds with the 20% highest "bond book-to-market ratios" outperform their lowest quintile counterparts by 3%-4% per year, other things equal. The finding controls for numerous attributes tied to liquidity, default, microstructure, and priced asset risk, including yield, credit spread, structural model equity hedges, bond rating, and maturity. If an efficient markets story explained the 3%-4% spread, we would not observe (as we do) rapid decay in the ratio's predictive efficacy with implementation delays beyond one month, efficacy across the bond-type spectrum, and an inability of microstructure, factor risk, and bond attributes to account for the anomaly.

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

A corporate bond's book value divided by its market price strongly predicts its return from actual transactions occurring at least eight days after observing the signal. Bonds with the 20% highest "bond book-to-market ratios" outperform their lowest quintile counterparts by 3%-4% per year, other things equal. The finding controls for numerous attributes tied to liquidity, default, microstructure, and priced asset risk, including yield, credit spread, structural model equity hedges, bond rating, and maturity. If an efficient markets story explained the 3%-4% spread, we would not observe (as we do) rapid decay in the ratio's predictive efficacy with implementation delays beyond one month, efficacy across the bond-type spectrum, and an inability of microstructure, factor risk, and bond attributes to account for the anomaly.

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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 book-to-market proxies for priced risk. For example, Berk (1995) points out that high risk firms discount future cash flows at higher rates, implying that high risk firms should exhibit both low market prices and high book-to-market ratios, other things equal. Thus, whenever alpha measurement imperfectly controls for risk, book-to-market will proxy for omitted risk factors and spuriously generate alpha. An equally plausible alternative is that, on average, high book-to-market ratios reflect underpriced shares, and low ratios reflect overpriced shares. This interpretation of book-to-market as a mispricing metric views book equity as a crude measure of equity fair value. Here, high book-to-market firms' high equity returns express rates that translate excessively low prices into future payoffs. If pricing mistakes rather than omitted risk factors account for book-to-market's relation with returns, alpha's correlation with book-to-market warrants active trading that exploits valuation errors.

To better understand book-to-market's role in asset pricing, we focus on an asset class that rivals stocks in importance: corporate bonds. Book-to-market's importance in equity pricing makes the ratio a natural starting point for studying the drivers of corporate bond returns. We define the "bond book-to-market ratio" ("BBM") as the bond's book value per unit of face amount divided by the bond's market price per unit of face amount. This metric predicts a bond's returns, whether raw or adjusted for risk.

Corporate bonds possess unique attributes that aid understanding of why book-to-market influences asset returns, like equities. For one, fair prices for bonds are easier to infer than for equities. Indeed, bond dealers typically infer quotes and marks for bonds with "matrix pricing"—in which a bond's fair price is a time varying function of many bond characteristics that influence other bonds' prices. Matrix pricing of a bond's fair value is only possible because the magnitude and timing of bonds' future cash flows are more transparent than those of equities. The future cash flows of many bonds are known with relative certainty; for the senior bonds we focus on, only extreme and infrequent outcomes for the economy or a company materially affect the likelihood of meeting payment promises. Discount rate variation has far more influence over these bonds' monthly returns than changes in cash flow projections, facilitating risk measurement compared to equities. Thus, it is difficult to entertain risk mismeasurement as the source of BBM alpha spreads that are almost as large as the alphas book-to-market generates for stock. Nor can a risk story explain why the equity-hedged bond returns implicit in corporate bond structural models exhibit the same magnitude BBM anomaly as unhedged bond returns.

Liquidity differences do not explain the anomaly either. High BBM bonds tend to be more heavily traded than their low BBM counterparts. For the large trades of institutions, round-trip trading costs are about the same (5 bp higher for high BBM), each bond's bid-ask spread is used as a control variable, and high bid-ask spread bonds exhibit about the same BBM return predictability as low bid-ask spread bonds.

BBM starts at one when a bond is issued. Most bonds' coupons are set so that a bond's book value at issue and face amount paid at maturity are approximately the same—referred to as a "par bond." Over time, the book-to-market ratios of formerly par bonds then rise above one (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 could generate price deviations from those schedules.

If sentiment has a large effect on a bond's price, the effect is unlikely to persist for long, as arbitrage and mean reversion in sentiment itself forces convergence to fair value. Hence, low book-to-market ratios 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. If sentiment-based price distortions apply to only a few of the extreme BBM bonds, price distortions for those few must be large to drive the BBM effects seen in the portfolios containing them. In this case, a persistent characteristic, like BBM, will likely influence returns for a short period of time. Prices for the vast majority of extreme BBM bonds have no reason to similarly converge if they were priced fairly from the beginning. Such rationally priced bonds are merely caught up in extreme BBM's wide net. By contrast, if BBM proxies for omitted risk or liquidity controls, which are more stable characteristics, BBM should predict returns even if implemented with substantial delay.

BBM's evolution parallels that of the bond's yield-to-maturity ("YTM"). At issuance, the YTM of the ubiquitous par bond matches its coupon rate. If its subsequent return exceeds its initial YTM, its BBM and YTM will fall, and vice versa. Like BBM, YTM is a transformation of a bond's price, but neither directly maps into an expected return. YTM, particularly when deployed as a function of rank-based dummy variables, better captures expected returns than the cruder BBM. Nevertheless, when controlling for YTM ranks along with a host of other variables, including past returns, duration, credit spread, liquidity, and default likelihood, the highest BBM bond quintile outperforms the lowest by almost 4% per year.

The study of corporate bonds has heretofore been hindered by their relatively thin trading, which makes it difficult to use transaction prices to measure monthly returns and strategy performance. We employ transaction prices from the relatively comprehensive TRACE database. To overcome the obstacle of thin trading, we apply the martingale property of informationally efficient asset prices, establishing hypothetical mid-market prices from the first and last transactions within the month of the return. The prices imputed from these intra-month transactions go into the numerator (end-of-month price) and denominator (beginning-of-month price) of each bond's monthly return calculation.

Prior studies employing TRACE focus mostly on its most liquid bonds.[1] Constructing monthly returns for bonds that trade nearly every day, often multiple times, is straightforward. However, studies of such bonds cannot draw unbiased conclusions since liquidity could be correlated with bonds' returns or control variables. Filtering a sample ex-post for its most liquid bonds could lead to conclusions that do not even apply to the narrow set of bonds studied. By contrast, our analysis of liquidity's impact lacks bias because the filter is based on past trading activity. Indeed, as one robustness check, we report results for bond subsamples that are more liquid, obtaining results that are similar to those for all bonds.

If a bond's current yield (coupon/price) matched the bond's expected return, the bond's "flat" price, i.e., price excluding accrued due, would perfectly follow a martingale. In this case, a bond's imputed beginning- and end-of-month flat prices generate noisy return estimates with a slight upward bias due to Jensen's inequality. The noise is small, as most imputed prices are from transactions occurring within a few days of the month's start and end.

When current yields do not fully reflect a bond's expected return, the flat price will not follow a martingale. For example, riskless bonds issued at par can become discount bonds, generating higher BBMs when interest rates increase and vice versa. Yet, both discount and premium riskless bonds have flat prices that converge to par at maturity. Such violations of the martingale hypothesis only serve to strengthen our findings. Using the intra-month flat prices to compute returns of high BBM bond tends to understate their full-month return, while using low BBM bonds' imputed prices tends to overstate their full-month return. The same insight applies when market-wide credit spreads expand or shrink since issuance. Hence, the BBM anomaly we discover from the return spread imputed with intra-month prices conservatively estimates the true return spread for the full month. As a robustness check, we verify that the BBM anomaly remains for returns from dealer-quoted end-of-month mid-spread prices.

The risk-adjusted profits from the BBM trading strategy with monthly rebalancing do not survive transaction costs, which are higher for corporate bonds than for stocks. These transaction costs may deter hedge funds and other short-term arbitrageurs from exploiting the BBM strategy, whether we estimate the costs from the prices of all trades between dealers and customers or only from those with volumes exceeding 100,000 U.S. dollars. Nevertheless, a buy-and-hold variation of the strategy survives the transaction costs incurred by larger trades, enhancing overall net performance provided the institutions avoid

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

additional short sales costs and constraints. Merely tilting a long-only portfolio towards underpriced and away from overpriced bonds to some degree can avoid short sales and enhance performance given the degree of mispricing observed.

Alongside an abundant 50-year literature on equity market efficiency is a sparse understanding of the informational efficiency of the bond market, which is fundamental to a comprehensive portrait of asset pricing.[2] 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 et al. (2014) document that forward rates do not span risk premia. Cieslak and Povala (2015) enhance this return predictability by accounting for long-term inflation. In the cross-section, Asness et al. (2013) uncover value and momentum effects in government bond indices, while Brooks and Moskowitz (2017) find that value, momentum, and carry factors help predict government bond returns outside of the U.S. Finally, Brooks et al. (2020) show that exposure to traditional risk factors largely explains the active returns of fixed income managers.

Research on whether corporate bonds reflect public information and on corporate bond characteristics that account for the cross-section of corporate bond returns is nascent. Gebhardt et al. (2005) report that bonds with high default risk and distant maturities earn higher returns. Chordia et al. (2017), Jostova et al. (2013), Bai et al. (2019), and Bali et al. (2019) show that bond returns are correlated with past bond returns. Choi and Kim (2018), Israel et al. (2018), Avramov et al. (2019), and Bali et al. (2020) study factors and anomalies in bond markets, while Bretscher et al. (2020) show that corporate finance puzzles are resolved with better estimates of firms' market capital structure. Research on bond book-to-market is sparse. Israel et al. (2018) refer to the yield spread within credit categories bonds as "value." Houweling and van Zundert (2017) use a bond book-to-market factor in a robustness test.

We estimate bond trading profits adjusted for risk with two approaches. The first is cross-sectional Fama and MacBeth (1973, FM) regressions. These control for bond attributes, such as yield-to-maturity, credit ratings, nearness to default, duration, credit spread, coupon, maturity, value outstanding, bond past returns, and liquidity, along with several equity attributes tied to equity returns. We also employ time series factor models. The latter include Bai, Bali and Wen (2019, "BBW")'s factor model, both with and without augmentation by a term structure factor, and a customized 21-factor model subsuming the union of Houweling and van Zundert's (2017) and Bektić et al. (2019)' s factors. The BBM strategy's profits remain

[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 et al., 2011), profitability (Novy-Marx, 2013), and mispricing from peer-implied accounting statement and equity market capitalizations (Bartram and Grinblatt, 2018, 2021). Harvey et al. (2016) and Green et al. (2013) document more than 300 stock return predictors.

significant with factor risk adjustments and, like equity book-to-market, are larger for "small bonds" (i.e., those with below median market capitalizations).

The risk-adjusted profits we document are not contaminated by market microstructure biases or by 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 et al. (2019). For the 20% of bonds that are closest to default or least liquid, the BBM signal has about the same efficacy as it does for the complementary bonds in the sample. The irrelevance of default risk and liquidity for BBM efficacy casts doubt on an omitted risk or liquidity factor explanation of the BBM anomaly. Moreover, for government bonds, BBM offers no return predictability, indicating that our controls are adequate for capturing the return effects of the term structure. We also demonstrate that imputing monthly returns for government bonds, computed from their intra-month prices at the transaction dates of our sample's more thinly traded corporate bonds, leads to the same "non-result." Thus, the martingale assumption is innocuous. Finally, we show that the efficacy of the BBM signal for corporate bonds decays rapidly as the signal becomes stale. As noted earlier, the rapid decay in efficacy, particularly when compared to the slower evolution of the BBM attribute, is more suggestive of mispricing rather than risk mismeasurement or liquidity differences 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.

I. Data and Methodology

Prices for signals and bond returns largely come from the enhanced (pre-April 2020) and standard TRACE databases. Robustness tests also analyze Merrill Lynch month-end trader marks, with the same start month as TRACE, but ending December 2016, covering 140,808 bond-month observations. The TRACE data are 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] Most analysis is limited to senior, unsecured, fixed-coupon bonds with no embedded options other than (typically, make-

[3] While TRACE data commence in July 2002, our performance analysis commences in February 2003 to ensure data on the bond momentum control. Merrill's data contain month-end marks for bonds that did not trade in the month.

whole) call provisions (e.g., BBW, 2019; Chung et al., 2019). Some tests study all TRACE fixed-coupon bonds. Both TRACE samples exclude transactions reported to occur before the bond's issue date or after its maturity date, those reported as cancelled, those attached to non-U.S. firms or denominated in non-U.S. currency, and those from bonds issued by financial firms (SIC codes 60-69).[4] We modify prices or other terms to be corrected values when TRACE indicates a retroactive correction. Following BBW (2019), we also remove transactions with prices below 1/20 or above 10 times their face amount, bonds with remaining maturity of less than one year, and bonds in default at the time of BBM signal implementation. For BG signal analysis, the issuing firm must have a single common equity share class of a U.S. corporation (share classes 10 and 11) in the CRSP Monthly Stock File, have a share price of at least $5, a positive number of common shares outstanding listed on the NYSE, Amex or Nasdaq, and positive total assets on the days of BG signal implementation.

For the TRACE data, which are daily, we analyze the profitability in month $t + 1$ of trading signals, primarily BBM, from information known by month t's end. Imputed prices from month $t + 1$ transactions help estimate full-month $t + 1$ returns. Unlike prior studies, we require a minimum eight-day gap between the transaction date of the bond price used for the signal and the first day of the next month. The latter is the earliest transaction date we might use for month $t + 1$'s return imputation. As discussed later, this lengthy separation, an enhancement of measures used in equity studies to avoid bid-ask bounce, prevents microstructure biases from contaminating our findings. Note that it is merely the price inputs for the signal and estimated return that require separate and distant transactions. The signal is known and assumed to be implemented at month-end.

A. Return Construction

Unlike equities, bonds trade infrequently and often at large bid-ask spreads. To address these issues, we apply the martingale property of asset prices. 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 the impact of risk premia, time value of money, and any payouts between the dates. These adjustments are small and closely captured by a bond's interest earned when transaction dates are close to the month-end price estimation date.[5]

TRACE reports bond transactions' flat prices. Unless a bond is in default, a bond buyer pays the sum of the flat price and interest accrued, known as the "full" price. The full price return plus any paid coupon

[4] Researchers typically exclude financial firms because these firms are structured around leverage and would dominate the results if included. Moreover, many firm characteristics, like profitability, are not comparable with non-financial firms.

[5] Note that the martingale property holds only under the null hypothesis of market efficiency. Behavioral-based return anomalies are evidence that rejects efficiency, but the alternative hypothesis are irrelevant for classical statistical tests.

is an unbiased estimate of the bond's expected return. Thus, if earned interest per dollar invested—the month's difference in accrued owed plus any paid coupon—fully captures the expected return, the flat price must follow a martingale. While monthly changes in accrued interest plus any distributions do not perfectly match the compensation for the time value of money and risk, they are close approximations, particularly over short time period, typically a few days. Portfolio diversification makes the approximation more innocuous. Finally, any failing of the martingale hypothesis implies that our results are conservative, as explained in the paper's introduction. These insights validate substitution of flat bond prices from transactions at nearby dates for the month-end flat prices that would be experienced by the same bond if the data were available. Specifically, a bond's month $t + 1$ return is its flat price change from the first and last transactions in month $t + 1$ per dollar invested plus the current yield from holding the bond over the entire month. Details are provided below.

End-of-month Flat Bond Prices. The martingale property implies that the estimated end-of-month flat bond prices, P^E, are the mid-market end-of-month flat prices at which the bonds would trade plus noise. The noise depends on 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 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 April 30, 2013 flat price, we might use the flat price of an April 26, 2013 trade. If there is no month $t + 1$ transaction for bond *j*, we treat the bond's month $t + 1$ return as missing.

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

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

$$R_{t+1} = \frac{P^E_{t+1} + AI_{t+1} + C_{t+1}}{P^B_{t+1} + AI_t} - 1, \tag{1}$$

where P^B_{t+1} and P^E_{t+1} are the beginning- and end-of-month $t + 1$ imputed flat prices, AI_t is accrued interest owed at the end of month t, and C_{t+1} is the coupon (if any) awarded for holding the bond in month $t + 1$. We 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, a momentum control variable, are computed analogously to equation (1), i.e., the return comes from a single beginning and end price over the past return horizon. Analogous to equation (1), the six-month return used as a momentum control is adjusted for beginning and ending accrued interest, as well as any coupons paid during the interval.

Due to Jensen's inequality, noise in Equation (1)'s denominator, arising from beginning price imputation, upwardly biases its return estimates—analogous to the upward bias in equity returns shown in Blume and Stambaugh (1983). However, our results are based on the return spread between two quintile portfolios. If the 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. This is distinct from the conservativism generated by martingale hypothesis violations. Recall that the latter conservativism is generated by discount (high BBM) bonds having flat prices that tend to appreciate, meaning partial month flat price changes understate full-month flat price changes; likewise, premium (low BBM) bonds' imputed flat prices, which tend to depreciate, overstate full month price changes. The imperfections in our analysis thus imply wider BBM return spreads than reported.

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 cannot 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.[6] 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 exists for the few bonds that are issued at deep discounts. Fewer than 0.1% of bonds have offering prices below 50, and 99.8% have offering prices above 90. Moreover, the average issue prices of the five BBM quintile portfolios are all close to 99.5. The flat prices of such original issue

[6] Specifically, if the imputed beginning-of-month price is quoted flat due to default, equation (1) substitutes the flat price of the first transaction preceding the transaction used for the signal (hence, pre-default) as P^B, uses the end-of-month (hence, post-default) price for P^E, and omits accrued interest and coupons in the numerator. This understates the return of the BBM portfolio we take a long position in and has no effect on the short position (which lacks defaulted bonds).

discount bonds appreciate rather than (approximately) follow a martingale. However, sizable discounts are rare, the numbers of days of amortization are generally small, and the distribution of such bonds across BBM quintiles is relatively symmetric. For these reasons, adjusting the martingale price estimate for original issue discount bonds would increase the returns of BBM quintile portfolios by only negligible amounts. Eschewing the adjustment, as we do, has no detectable effect on the return difference between any pair of quintile portfolios and helps offset the Jensen's inequality bias discussed earlier.

B. Signal Construction

Price measurement error shared by the month-end signal and subsequent return generates correlation between the two. Constructing end-of-month t signals from transaction prices at least 8 calendar days before the first day of month $t + 1$ avoids this pitfall. The multi-day gap addresses trade splitting and workouts. Consider a 120 million USD customer bond sale to one or more dealers executed as three 40 million USD sales on three consecutive days: April 29, 30, and May 1. Such trades yield three daily price estimates at the dealer bid, assuming no other trades in the bond. The bid price artificially inflates BBM computed from either the April 29 or 30 transaction prices, as well as the return initiated at May 1's price. Similar concerns exist if a dealer gives favorable off-market pricing to a series of trades straddling month end. These scenarios may be rare but become less likely the larger the gap between the prices used for signals and returns. An ultra-conservative eight-day gap ensures that correlations between estimated BBM and estimated returns are due to a signal predictive of true returns rather than any microstructure bias.

Bond Book-to-Market Signal. The book value per \$100 face amount, an adjustment of the bond's issue price, is sourced from Mergent's Fixed Income Securities Database (FISD). Table 1 Panel A reports the distribution of issue prices. For most bonds, the FISD issue price is near \$100.[7] If the bond is issued at a discount or premium, we apply the accounting rule that linearly amortizes the premium or discount to maturity on month-end dates to arrive at the bond's (end-of) month t book value. For 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. P^S, the signal's flat price per \$100 of face amount, is taken from the bond's most recent transaction, (excluding the last seven days of month t). The approach employs some prices from fairly stale trades, but since the information represents what is available at the end of month t, it can direct trades at that instant in time. It is also conservative, since signals based on stale prices are likely to be less effective. Table 1 Panel B reports the distribution of time between the transaction price

[7] BBM's ability to predict returns is highly significant, but slightly reduced, if 100 substitutes for the bond issue price.

[8] With all FM regression controls, the BBM Q5 – Q1 return spread is 32 bp per month for the FISD subsample focused on in the paper, but 25 bp for the subsample lacking FISD issue price data, with 100 assumed as book value.

date used for P^S in the Book/P^S signal and the transaction used for beginning price P^B in the bond's month $t + 1$ return estimate. For the senior unsecured bonds that researchers traditionally study ("Traditional Bonds") and that we focus on, the median gap between the signal date and that latter price is 11 days; the average is 16 days (Panel B's first row). About 10% of the gaps exceed 25 days.

Figure 1 depicts the transaction timing of the prices used for signal and return construction. P^S represents the transaction price used for month t's signal, P^B and P^E are beginning and end prices for month $t + 1$'s return. The figure illustrates the dates of four consecutive transactions in the bond as red dots. 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 flat prices for month $t + 1$ returns come from intra-month transactions.

Bartram and Grinblatt Mispricing Signal. We later study 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 transactions less than eight days before the first day of month $t + 1$), plus the aggregate book value of firm i's other liabilities.

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

C. Alpha Tests for Signal Efficacy and Control Variables

The BBM and BG signals are used to 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 $t + 1$'s bond returns within these quintile portfolios. We test for the alpha generating efficacy of the signals employing FM cross-sectional regressions as well as structural and factor models.

FM Regression Coefficients on BBM (or BG). Here, the monthly regression's unit of analysis is the bond. We cross-sectionally regress a bond's month $t + 1$ return (computed with Section I.A's procedures) on BBM (or BG) 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 contain 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/liquidity controls that are measured in the return period, month $t + 1$. We employ four main specifications of nonparametric regression controls. The first has industry controls, the second adds market microstructure controls; the third adds controls for bond characteristics; the fourth adds equity characteristics of the bond issuer. The many controls in category-oriented FM regressions represent a high dimensional matrix classification of each bond, akin to matrix pricing commonly used by Wall Street to mark YTMs and prices of thinly traded bonds. Internet Appendix A describes these characteristics in more detail, along with the 28 items used for the BG signal.[9] A robustness check with a necessarily shortened sample period and smaller cross-section includes the bond's past 3-year return, skipping a year ("bond long-term reversal").

Equation (1)'s estimation noise from flat price imputation generates no bias in FM slope coefficients. Because the dependent variable R_j is bond j's true (but unobservable) full month return r_j less mean zero noise, e_j, regression of the latter on an observable attribute X_j

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

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

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

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

Structural Models. FM regressions can also be combined with structural models. Structural models view corporate bonds and equity as contingent claims on the firm's assets. One typically uses the models to calculate bond prices, yields, or credit spreads, but they also have implications for returns. Here, structural models imply that corporate bond returns should be perfectly correlated with a portfolio of riskless

[9] The 28 BG signal items at the bottom of Appendix A are the same regressors used in BG's (2018) signal. Point-in-time data ensure that the information used to estimate debt fair value was available to investors when the mispricing signal motivates a trade.

bonds and same-firm equity.[10] Hedging out the equity component on the left-hand side of the FM regression adjusts for most of the risk premium linked to credit risk. To identify hedge ratios, we run a panel regression of bond returns on their own-equity returns interacted with the control dummies used for the FM regression. This generates equity hedge ratios for each bond-month observation from the panel's coefficients and monthly bond attributes.

Factor Model Intercepts. Intercepts from regressing the time series of excess returns (above 1-month LIBOR) of five BBM quintile portfolios on factor portfolio returns is an alternative to FM regressions for risk adjustment. The regression intercepts or spreads between them represent alpha and should be zero in an efficient bond market. We begin with BBW's (2019) five factors: the bond market, credit, downside risk, liquidity, and reversal factors. Their construction, using bond data from TRACE, follows BBW's (2019) procedures.[11] Data from Merrill Lynch is required for downside risk in the sample's first three years, when the factor requires data that precedes TRACE's initiation. In addition, we use an Augmented BBW 6-factor model that further adds a term structure factor to BBW's five factors, and a customized 21-factor model consisting of 13 equity and eight bond factors.[12]

D. Summary Statistics for the Overall Sample

Table 2 Panel A reports summary statistics for BBM and other attributes of the senior unsecured bonds and their issuing firms. Each row reports the time series average of cross-sectional means of each variable using all bonds (Column 1) and all bonds within each BBM quintile (Columns 3-7). Q1 represents bonds

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

[11] Specifically, we first calculate volume-weighted average daily prices of all bonds in TRACE and Mergent FISD that meet the BBW (2019) filters. We then construct each bond's monthly return series as follows: If TRACE reports a bond trade in the last five business days of months t and $t + 1$, we compute its return from consecutive month-end prices as given by its last daily volume-weighted prices in those months (adjusting for accrued interest and coupons paid). If the end-of-month t price is unavailable, we compute month $t + 1$'s return using the earliest (volume-weighted average) daily price in the first five business days of month $t + 1$ as the return's beginning price. If neither beginning nor end price is available, we treat month $t + 1$'s return as missing. Finally, like BBW, we form factors by face-value weighting the returns of specific subsets of bonds using BBW's factor criteria.

[12] The equity market factors include all five equity factors of Fama and French (2015); 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 issuers 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 et al. (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.

with the smallest 20% of BBM, averaging a BBM of 0.85; Q5 represents the highest BBM quintile, averaging a BBM of 1.10. Column 2 also reports the time series average of the cross-sectional correlations of the characteristic with BBM.

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 credit ratings (AAA=1, …, D=22, with 10 or less indicating investment grade) and are closer to default.[13] They also have higher YTMs, lower market value outstanding, higher bid-ask spreads, more trading volume, larger numbers of trades, 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.[14] 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 first two rows correspond to equal- (EW) and value- (VW) weighted quintile portfolio returns, respectively, both of which exhibit nearly monotonic increases across BBM quintiles. For example, the lowest BBM EW quintile portfolio earns 57 bp per month, while the highest earns 101 bp per month. Panel B also shows the average monthly return for the full sample (66 bp EW and 57 bp VW, a more than 1% annualized difference), the average monthly cross-sectional correlation between returns and BBM (0.04), the average monthly spread between the returns of the largest and smallest BBM quintiles (44 bp EW and 41 bp VW, both significant), as well as the fraction of months with a positive Q5 – Q1 return spread (63% EW and 59% VW, both significant). The t-statistics of the spread correspond to annualized Sharpe ratios of 0.92 (EW) and 0.85 (VW), respectively. The last two rows of Table 2 Panel B

[13] 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.

[14] 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).

show the breakdown of the top rows (EW) by bond size. Small bonds have larger returns within each quintile and a larger BBM effect than large bonds.[15] The small bond BBM effect comes from Q5, for which the small minus large bond return is 27 bp per month—nearly twice the small minus large spread for Q1 and the largest size spread for any quintile.

Table 2 Panel C, sourced from TRACE, reports each BBM quintile's joint distribution of beginning and end bid-ask pairs for month $t + 1$'s returns. It reports the fraction of returns that derive from the nine pairings of bids (customer sell to a dealer), asks (customer buy from dealer), and mids (dealer-to-dealer transaction) of beginning and ending prices. A bid beginning price tends to have a higher return, while a bid ending price tends to have lower return, with the reverse for asks. Applying the bid ask spread from each quintile (Panel A) to the joint distribution in Panel C implies that both quintile 1 and 5's returns are upwardly biased, by 1 bp and 3 bp, respectively. Their difference, 2 bp, is negligible. Hence, Table 2 Panel B's returns are not driven by return computation that sometimes rely on bid and ask prices.

Similarly, the BBM anomaly does not stem from persistent off-market prices that only favored clients can trade at. Such favored prices would artificially inflate month t's BBM. As shown later, BBM risk-adjusted return spreads for returns generated by dealer-to-dealer transactions are about the same as those generated by customer buy and sell transactions.

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

While the relatively low volatility of bond returns makes Table 2 Panel B's 5% annualized BBM-based spreads look large, many return-influencing risk attributes correlate with BBM. For this reason, we need to analyze the marginal effect of BBM controlling for other attributes. Both cross-sectional FM regressions and time series factor model regressions show that BBM is not a proxy for return-predicting attributes or factor betas.

A. Fama-MacBeth Cross-Sectional Regressions

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

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

In equation (2), $BBM_{j,t}$ is the month t BBM signal for bond j, and $X_{j,s,t}$ is the end-of-month t value of characteristic s of bond j (or its issuer), including industry fixed effects. The FM procedure averages the

[15]Although these two rows sequentially sort on BBM and then on bond value, they do not perfectly average to the top row because some bonds lack data on face amount outstanding.

monthly coefficients over time and tests whether the average significantly differs from zero.

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

Specifications 1 and 2 regress bond returns on BBM and industry dummies. Specifications 3 and 4 add a set of market microstructure/liquidity controls to Specifications 1 and 2 that roughly proxy for the precision with which the martingale approach estimates month $t + 1$ returns. They include the number of bonds from the issuing firm in month $t + 1$, the percentage of the market value of the issuing firm's bonds with month t signals that trade in month $t + 1$, and a pair of controls for the (absolute value of the) number of calendar days between the first (last) day of the month and the transaction date used for beginning-of- (end-of-) month $t + 1$ prices. Specifications 5 and 6 add bond attribute controls to Specifications 3 and 4. 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 issuer, as well as its accruals, earnings surprises, gross profitability, and earning yield—all popular controls in the finance literature.[16]

All specifications tell a similar story about BBM's role in 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. Omitted for brevity, the relatively small effect of the market

[16] See Banz (1979) and Fama and French (1992) for size, Rosenberg et al. (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 surprises, 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.

microstructure regressors applies to the remaining two specifications as well. This suggests that our martingale procedure for identifying month $t + 1$ returns is unlikely to have distorted inferences. The addition of bond-specific controls (Specifications 5 and 6), measured (in contrast to the signal's 8-day gap) as closely to the end of month t as possible, reduce BBM's influence on a bond's month $t + 1$ return by about two fifths, but the BBM effect remains highly significant. Specification 7 and 8's addition of controls related to equity returns increases the BBM Q5 coefficients by about one fifth compared to Specifications 5 and 6, and also increases their significance. Specifications 7 and 8 also establish that equity book-to-market does not predict bond returns once BBM is controlled for.[17]

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

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

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

[17] 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.

and far more significant alpha spread of 50 bp per month, but this finding has potential biases from common errors in the marks used for both BBM and returns.

Structural Models. Table 3 Panel B also rebuts claims that Table 3 Panel A's significant alpha spreads stem from failure to control for the structural model implication that distressed bonds resemble equity. Earlier, we refuted the argument that BBM Q5 bonds are distressed, thus resembling equity (while Q1 bonds mimic risk-free debt) by pointing out that Q5's bonds exhibit negligible default rates. We also noted the extensive controls for credit spreads, bond rating, and default in Table 3's FM regressions. Punctuating our claim is Column 4 in Table 3 Panel B, which reruns Panel A's Specification 7 (all controls) with equity-hedged bond returns as the dependent variable. Bond j's month $t + 1$ hedged return subtracts the product of its end-of-month t hedge ratio (described earlier) and the issuing firm's month $t + 1$ equity return in excess of LIBOR from the bond's month $t + 1$ return. The hedge eliminates the bond's asset risk premium component. Column 4's results here are highly similar to Table 3 Panel A. BBM Q5 outperforms Q1 by 32 bp per month ($t = 4.82$) with a same-firm equity hedge. The similar equity hedged and unhedged BBM quintile coefficients indicate that structural models are unlikely to play a successful role as supplements or replacements for Table 3's categorical regressors. Finally, if BBM Q5 merely proxied for poor default controls, BBM should predict the firm's equity return. However, Table 3 Panel B (Columns 5) shows that the BBM Q5 coefficient of –0.082 is insignificant ($t = -0.71$) with the firm's equity return as the dependent variable.[18] In sum, BBM predicts bond returns and equity-hedged bond returns, but not same-firm equity returns. Later study of interaction effects supports this finding.

Liquidity premia. Could BBM Q5 outperform Q1 because it commands a large liquidity premium? Table 3 Panel B refutes this by rerunning Table Panel A's all controls regression after conditioning on bonds trading in month t. Column 6 shows these relatively liquid bonds have a BBM alpha spread of 32 bp per month ($t = 4.05$), which is identical (with the rounded values reported) to Table 3 Panel A's spread.

Long-term return reversals. Daniel and Titman (2006) and Gerakos and Linnainmaa (2017) note that 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 et al. (2019) show that a bond's 3-year past return, measured from months $t - 48$ to $t - 13$, strongly predicts return reversal. We omitted the 3-year past return as a control because it limits sample size: Requiring 48 months from the sample's beginning date halves the average number of bonds in the cross-section and cuts 42 months from the sample period. Nevertheless, in horse races between 3-year past return and BBM, using Table 3 Panel A's key specifications (plus the 3-

[18] The equity premium associated with default reflects outcomes where equity is nearly wiped out. Using a dummy for whether the equity return is below –75% as the dependent variable yields a BBM coefficient of 0.079 ($t = 1.50$).

year past return), the 3-year past return's coefficient is never significant and always economically small. For example, in specifications analogous to Table 3 Panel A's specifications 5 and 7, the 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. These results, based on a shorter sample period with fewer bonds than Table 3, suggests that BBM subsumes the 3-year past return effect as a predictor of corporate bond returns.

B. Factor Model Time Series Regressions

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

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

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

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

BBW Factors. The BBW 5-factor model has factors that control for overall bond market risk, credit risk, downside risk, liquidity risk, and short-term bond return reversal; the Augmented BBW 6-factor model adds a term structure factor. The first row of each of Panel A's top half (EW portfolios) and bottom half (VW portfolios) shows each quintile's BBW risk-adjusted returns. Table 4 Panel A's EW 19 bp alpha spread is smaller than the alpha spread (BBM Q5 coefficient) from any of Table 3 Panel A's odd-numbered (non-parametric) specifications, including the two lowest: Specifications 5 and 7 report alpha spreads of 27 and 32 bp per month, respectively. The VW alpha spread, 12 bp per month is even smaller than the EW spread and statistically insignificant. Part of the reason for the small EW and VW alpha spreads in Table 4 Panel A's 5-factor model is the BBW model's factor selection. It controls for some sources of factor risk, like credit risk, which reduce the Q5 – Q1 spread. However, it lacks a factor control for the term structure of interest rates, even though bonds with similar maturity tend to covary more with each other than with different maturity bonds. The BBW 5-factor model also lacks factors for many of the other controls in Table 3A's FM regression, like bond size. Table 2 Panel B showed that size is correlated with returns in each BBM quintile.

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 Panel A's FM regressions.

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

Bond Size. Table 4 Panel C reports the effect of size and alternative factor models. For brevity, factor betas are omitted. Panel C's top four rows illustrate the effect of bond size on factor model EW alpha with the BBW 5-factor and augmented 6-factor models.[20] With both models, bonds with less than intra-quintile median market capitalization have larger and more significant alpha spreads than bonds with larger value outstanding. With the 5-factor model, the large bonds exhibit no significant EW spread, as was the case with the VW spread in Table 4 Panel A. With the augmented 6-factor model (3rd and 4th rows), the small bond alpha spread is a significant 28 bp, which lies between the 27 and 32 bp alpha spreads from Specification 5 and 7 in Table 3 Panel A's FM regression. However, the 20 bp large bond spread, while

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

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

significant, is far smaller. If mispricing accounts for BBM alpha spreads, this finding, along with the comparable finding for the BBW 5-factor model, suggests that large bonds may be more efficiently priced than small bonds. The far greater efficacy of BBM as a predictor of risk-adjusted returns for small bonds mirrors a parallel finding for equities.

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

III. Understanding the BBM Alpha: Risk or Mispricing?

We now present additional evidence on the two competing explanations for BBM's return predictive success, as seen in Tables 3 and 4: first, that BBM proxies for an omitted risk or liquidity 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 or illiquid 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.

A. Signal Delay

Figure 2 plots alpha spreads (BBM Q5 dummy coefficients in Specification 7 of Table 3 Panel A) for signal delays ranging from zero to eleven months. In contrast to Table 3 Panel A, 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, ensures 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 Panel A, despite the shorter return series. Figure 2 also indicates that the alpha spread declines to about 9 bp 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 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.[21] 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. Like BBM, risk attributes move slowly. BBM strategy implementation delay of a few months should not decay as rapidly as Figure 2 indicates if an omitted risk attribute fully explained the findings of Tables 3 and 4.

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 5.3% annualized return spread observed. Generating Table 3's 3.8% annualized BBM alpha spread after non-parametrically controlling 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 to those of their more extreme neighbors.[22]

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 Panel A's results even when the quintile's remaining bonds trade at prices much closer to fair value.[23] When the highly mispriced

[21] 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.

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

[23] 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.

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).

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

Table 3 Panel A's extensive controls for credit ratings and nearness to default make it unlikely that an omitted credit risk control explains the BBM anomaly. Calibrations reinforce this argument. 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 EW return spread is 44 bp per month (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 per month alpha spread from Table 3 Panel A is twice as large as the YTM spread.

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

In all of Table 5 Panel A'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. The latter indicates that the 20% of bond most likely to default have a BBM effect that is statistically indistinguishable from the rest of the sample. For example, in Specification 7 of Panel A's top half, the bonds issued by the quintile of firms nearer to default have a 10 bp per month lower alpha spread than the bonds that are further from default. 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.

Table 5 Panel B shows that similar findings apply to liquidity. All but two interaction terms with the 20% least liquid bonds (Q5) are insignificant. The exceptions are marginally significant volume interaction term in Specifications 2 and 4, implying that the least liquid bonds exhibit stronger BBM normal score predictability, but only with limited regressor controls. More importantly, each of Panel B's 24 regressions demonstrates that all bonds, irrespective of liquidity quintile, exhibit a significant BBM effect. Next, we study whether omitted controls tied to the riskless term structure might explain our findings.

C. BBM and Lower Risk Treasury Notes and Bonds

BBM may also 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 Panel A using U.S. Treasury notes and bonds instead of corporate bonds.[24] 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 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 end price of that return, we compute Treasury security j's month t signal and month t +1 return using the latter security's end-of-day prices from days d_1, d_2, and d_3, respectively. All other transactions in the Treasury security are ignored, forcing it to exhibit the same illiquidity as its assigned corporate bond. We remove observations if day d_1 falls before the bond's issuance

[24] 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.

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 repeat Table 6 Panel D but randomly perturb 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 are highly similar.

D. Does BBM Factor Risk Explain the BBM Alpha?

According to Davis et al. (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 first row of the rightmost column 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.

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

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

A. An Alternative Signal Rooted in Mispricing

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

Table 8 reports coefficients on some of the key regressors in a pair of FM regressions that mirror Table 3 Panel A's kitchen sink specification. For comparison purposes, Table 8's first column repeats Table 3 Panel A's kitchen sink Specification 7, but narrows the sample to bonds issued by firms that have all of the accounting variables 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, and 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 Panel A's Specification 7.

The relatively small decline in BBM's alpha when the two signals compete indicates that the signals are "marginally quasi-orthogonal." By this, we mean that, controlling for other bond attributes, like yield-to-maturity, 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 Panel A's findings, we would expect BBM to lose almost all of its return predictive power once we include BG quintile dummies in the regression.

B. BBM's Return-Predictive Ability for All Bonds

Until now, our tests studied 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, 4 and 7'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 Panel A's FM regressions on the all bond sample, reports coefficients only for selected regressors of interest. Panel B repeats Table 4 Panel A and B's factor model regressions, reporting only the intercepts 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 Panel A. 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 Panel A Specification 7 is 32 bp ($t = 4.05$). Likewise, factor model alpha spreads between BBM Q5 and Q1—43 and 48 bp per month for Panel B, 28 and 28 bp per month for Panel C, all significant—exceed those from the restricted sample's factor models, as outlined in Tables 4 and 7, respectively. Thus, the BBM anomaly is stronger for the all-bond sample.

C. Off-Market Prices

One explanation for our results is that the TRACE-reported prices used to compute returns are available only to some investors rather than being fair estimates of mid-market prices. If this were true, customer transactions that give TRACE's beginning price for returns in quintiles 1 and 5 would generate higher BBM alpha spreads than dealer-to-dealer return initiating transactions. Table 10 refutes this conjecture using Table 3 Panel A's FM regression methodology. It adds interaction terms to the BBM quintile dummies for a return-beginning price that comes from a customer buy or sell transaction. The first column's 0.328 coefficient on BBM quintile 5 represents the Q5 – Q1 alpha spread when a dealer-to-dealer transaction inform the beginning price. 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 dealers.

D. 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).[25] Table 11 reports the factor model alphas (computed as in Table 4) of the five 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.

E. Transaction Costs

BBM's extreme quintile alpha spread before accounting for transaction costs is a useful metric for assessing bond market efficiency. However, bond price deviations from their fair values are not profit opportunities if transaction costs exceed gross profits. The corporate bond market's transaction costs are generally high (Chen et al., 2007; Edwards et al., 2007; Bao et al., 2011; Feldhütter, 2012). Therefore, alphas from the BBM signal may not be exploitable by arbitragers as a stand-alone trading strategy.

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 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

[25] 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.

bond. $T_{q,t}$ accurately estimates the bond-type's monthly effective half-spread. One of five $T_{q,t}$ values are assigned to each transaction, depending on the bond's quintile assignment.

To understand how transaction costs affect returns, one must combine them with portfolio 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 × 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 $\mathbf{D}_t$.[26] Each element of month t's difference vector is assigned one of five half-spreads tied to the quintile the bond belongs to throughout month t. If the j-th element of $\mathbf{w}_{q,t+1}$ is positive, bond j is assigned month t's effective half spread for bonds in quintile q. Algebraically, month t's transaction cost per dollar for updating quintile q's portfolio at the end of month t is

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

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 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 et al. (2011) show that corporate bond

[26] 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.

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. Net performance is the intercept from regressing quintile portfolio excess returns net of monthly transaction costs on factors. Subtracting transaction costs monthly alters factor betas, so Table 12's net performance does not exactly equal the difference between Table 4 and 11's average (gross) alpha and average transaction costs. 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,[27] 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. 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 monthly 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. BBW 5-factor net profits are still too low for all investors to exhibit significance, but 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 survives the transaction costs incurred by larger institutions, enhancing overall net performance. While institutions may also face additional short

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

sales costs and constraints, these can be avoided when merely tilting long-only portfolios towards underpriced and away from overpriced bonds.

V. Conclusion

Fundamental differences between the corporate 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 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 are held for long periods by their primary investors: pension funds, insurance companies, endowments, and mutual funds.

As a key first step to understanding both the information efficiency of the corporate market and book-to-market's effect on asset pricing, this paper studied book-to-market'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 low volatility of corporate bond returns compared to stock returns. Like equity book-to-market, small bonds exhibit larger BBM alphas, perhaps indicating that larger bonds are priced more efficiently. The paper presented evidence that the BBM trading strategy's alpha is unlikely to stem from an omitted risk, microstructure, or liquidity controls. This evidence leaves mispricing, particularly for small bonds, as the best explanation for the BBM anomaly. Supporting this explanation is 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 less liquidity, the irrelevance of callability and market microstructure controls, and the inability of BBW factor betas to explain BBM profits, even with an additional HML-like bond factor. Moreover, the riskless term structure cannot explain the BBM anomaly, as BBM does not predict U.S. Treasury returns—even when artificially forcing Treasury transactions data to mimic the sparseness of corporates.

We emphasize that our results are conservative. Trades are from signals that become known at least eight days prior to the start of the trade month, and we compute returns from intra-month transaction prices, eschewing "end-of-month" WRDS bond returns. This lengthens the time between signal and implementation by an average of about half a month. In addition, most of our focus is on senior unsecured bonds with, at best, simple call options (for which call exercise offers little economic advantage). This bond class exhibits negligible default risk. When we analyze a larger set of TRACE bonds that includes junior bonds, alpha spreads are considerably larger. Finally, we implement returns using the martingale assumption, violation of which lead to understatement of high BBM bond returns compared to low BBM bond returns.

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

The BBM anomaly's mispricing explanation may explain 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. Frictions, particularly information frictions, are greater for assets with small market capitalizations. In this light, the similarly higher degree of book-to-market efficacy for both small stocks and bonds is intriguing.

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. Of course, this assumes that both the bond and equity book-to-market premia stem from the same source: mispricing. However, given the many price-related anomalies in the equity literature,[28] including book-to-market, their anomalies could plausibly stem from the same phenomenon.

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

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

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

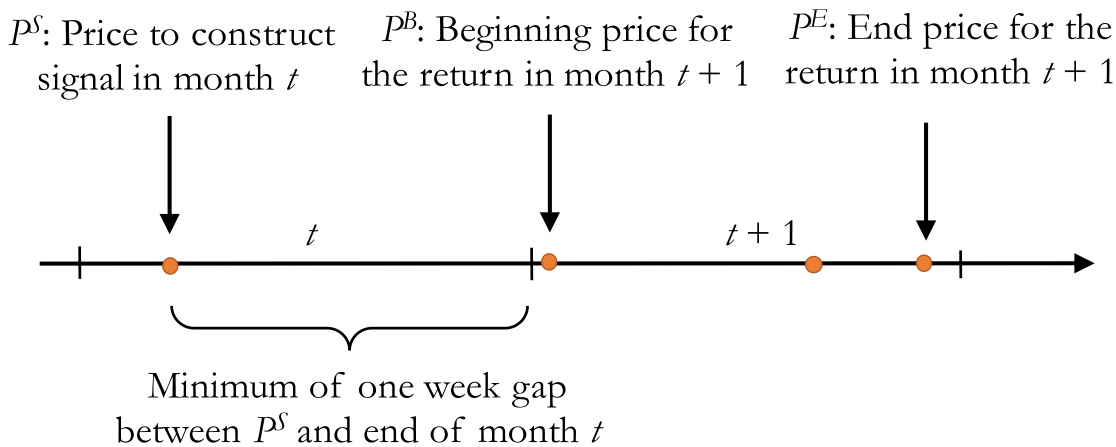


Figure 2: Signal Delay

The figure shows average coefficients from Fama and MacBeth (1973) regressions of monthly bond returns on bond book-to-market, controlling for other bond and equity characteristics (Specification (7) in Table 3 Panel A). Returns are regressed against 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 bonds 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.

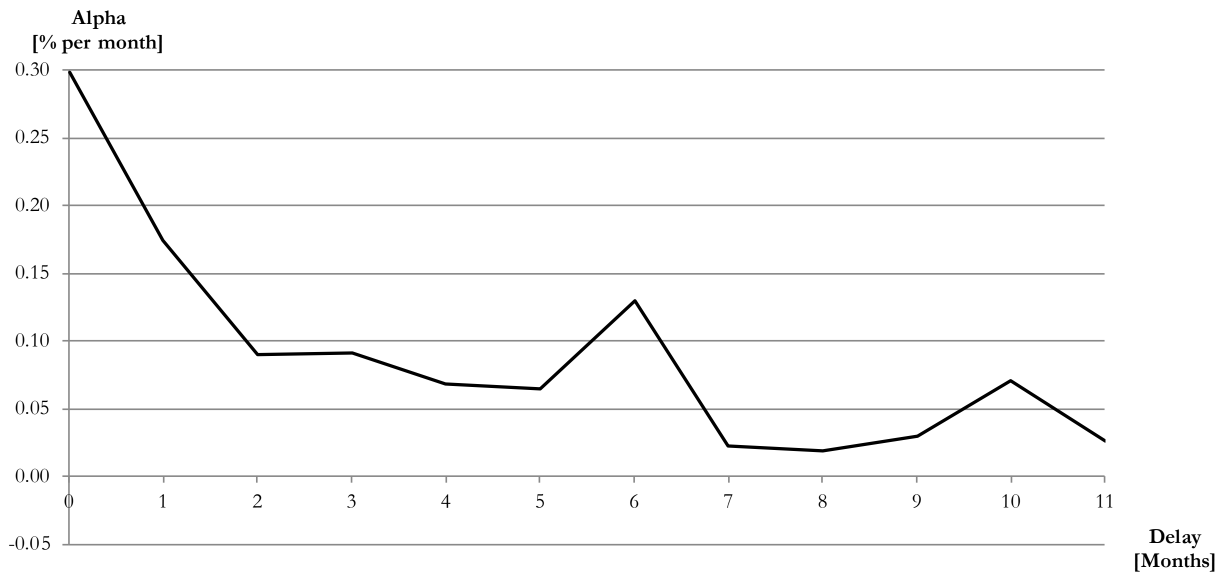
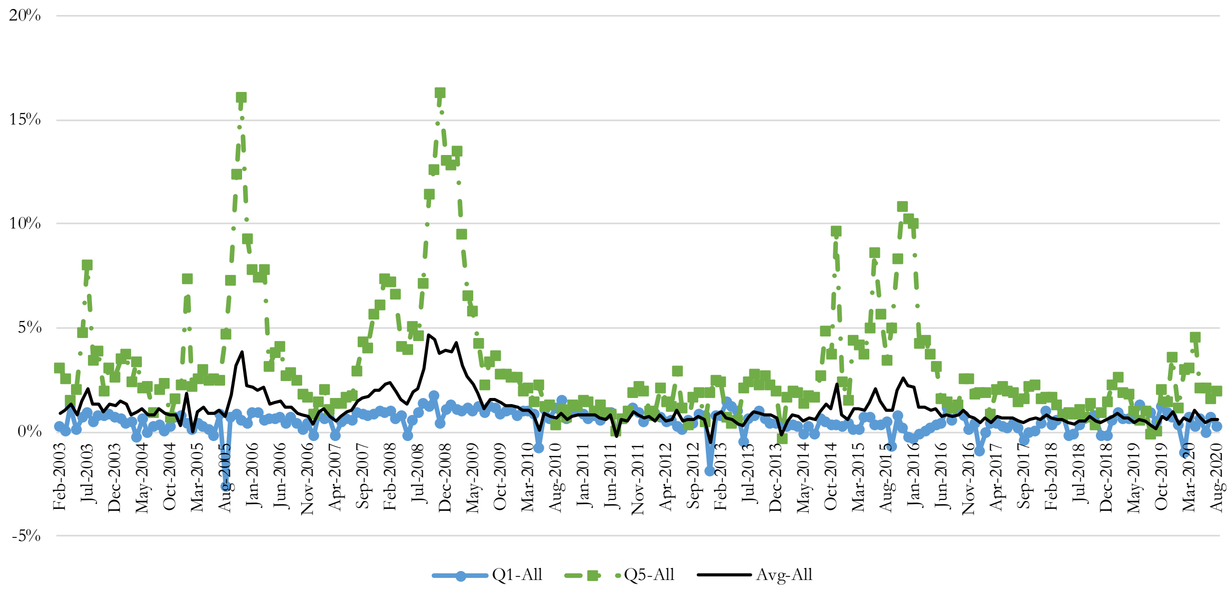


Figure 3: Monthly Bid-Ask Spreads for Bond Book-to-Market Quintiles

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 all quintiles.

Panel A: All Transactions



Panel B: Institutional Transactions

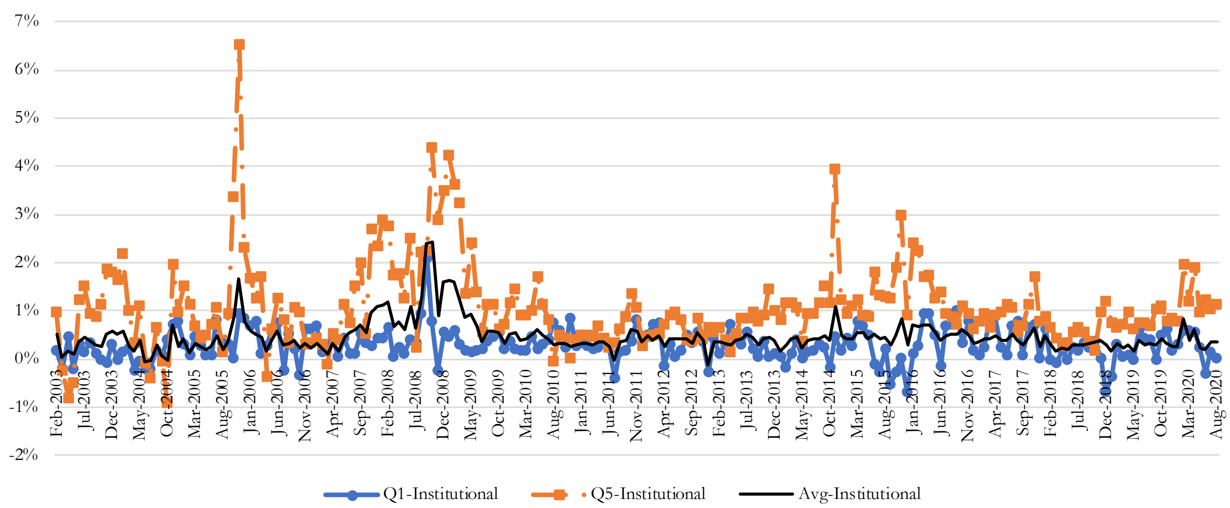


Table 1: Summary Statistics

The table reports statistics on the offering price of corporate bonds (Panel A), and the time difference between the transaction dates of the bond prices used to construct the bond book-to-market signal in month t and bond prices 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 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 and end 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 equally 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 and the fraction of positive Q5 – Q1 spreads. It reports results separately for all bonds, as well as bonds below ("Small Bonds") and above ("Large Bonds") the monthly median bond value from sequential sorts on BBM and bond value. Panel C reports the fraction of beginning and end prices for returns at bids, asks, and from dealer-to-dealer transactions by BBM quintiles. The fractions are scaled so that they sum to 100% for each quintile. The sample consists of nonfinancial firms with U.S. dollar-denominated, senior unsecured corporate bonds without embedded options other than call options. 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 Volume	49.23	0.10	33.08	40.35	47.66	56.20	68.86
Bond Volume Institutions	47.93	0.09	32.45	39.10	46.18	54.68	67.25
Number of Trades	103.1	0.14	56.94	93.42	111.1	118.9	135.1
Number of Trades Institutions	30.66	0.13	18.93	26.15	30.97	35.31	41.93
Bond Bid/Ask Spread	0.495	0.19	0.470	0.436	0.447	0.469	0.682
Bond Bid/Ask Spread Institutions	0.198	0.14	0.205	0.181	0.179	0.181	0.258
Number of Bonds	37.90	0.00	37.83	30.81	32.75	39.84	48.30
Number of Days from Beginning of Month	2.907	-0.08	3.899	2.843	2.602	2.587	2.741
Number of Days from End of Month	2.743	-0.08	3.727	2.714	2.478	2.413	2.508
Nearness to Default	-9.488	0.17	-10.10	-9.77	-9.479	-9.490	-8.605
Investment Grade	0.863	-0.24	0.954	0.910	0.869	0.854	0.726
Non-Investment Grade	0.137	0.24	0.046	0.090	0.131	0.146	0.274
Offering Price	99.49	0.05	99.23	99.49	99.55	99.61	99.56
Equity Mispricing	0.080	0.00	0.049	0.074	0.088	0.080	0.129
Equity Market Capitalization	2,720	-0.06	48,318	39,548	40,351	45,811	39,560
Equity Book/Market	0.652	0.20	0.591	0.601	0.604	0.640	0.825
Equity Beta	0.979	0.16	0.891	0.925	0.963	0.987	1.127
SUE	-0.003	-0.10	0.001	0.001	0.000	0.000	-0.016
Gross Profitability	0.226	-0.04	0.230	0.232	0.231	0.228	0.212
Earnings Yield	0.012	-0.28	0.056	0.053	0.047	0.038	-0.134
Equity Short-term Reversal	1.028	-0.03	1.067	1.061	1.051	1.053	0.910
Equity Momentum	10.59	-0.14	13.27	12.22	11.73	10.46	5.269
Equity Long-term Reversal	54.19	-0.10	58.54	58.03	56.28	54.01	44.13
Accruals	0.098	-0.03	0.093	0.105	0.112	0.107	0.077

(continued)

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

Panel B: Portfolio Returns

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

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

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

Table 3: Fama-MacBeth Cross-Sectional Regressions

The table shows results from Fama and MacBeth (1973) regressions of monthly bond returns on bond and stock characteristics and control variables. Across different specifications, returns are regressed against prior month values for bond book-to-market, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. Panel A employs quintile dummies for the characteristics as regressors except for bond book-to-market in even-numbered specifications, which employ the normal score of bond book-to-market. Each month's quintiles are determined from sorts of bonds with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for quintiles 2, 3, 4, and 5 of each characteristic, but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) for brevity. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. Panel B shows results for various robustness tests. Panel B Specification (1) uses parametric versions of the control variables, while Specifications (2)–(6) use non-parametric controls as in Panel A. Panel B Specification (2) uses the monthly bond return from trader marks provided by Merrill Lynch as dependent variable, while Specification (3) uses Merrill Lynch data to construct both the monthly bond return as well as bond book-to-market. In Panel B Specification (4), the regressand is an unbiased estimate of each bond's equity hedged return using the equity of the bond issuer. We estimate hedge ratios as the predictions of hedonic panel regressions of each bond's return on interactions between the monthly equity return of the bond issuer in excess of LIBOR and 131 dummies representing the bond's 61 (non-collinear) characteristics, including 38 industry dummies. The bond return component from flat prices is rescaled to alleviate biases from thin trading. The dependent variable in Panel B Specification (5) is the equity return of the bond's issuing firm. Panel B Specification (6) uses the same regression model as Panel A Specification (7), but restricts the sample to bonds that trade in month *t*. 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)

Panel A: Baseline Model

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

(continued)

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

Panel B: Robustness

			Non-Parametric Controls									
	(1)		(2)		(3)		(4)		(5)		(6)	
	Regressions with Parametric Controls		Bond Return (Merrill Lynch)		BBM and Bond Return (Merrill Lynch)		BondReturn – HedgeRatio * (StockReturn - Libor)		Stock Return		Liquid Bonds	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Bond Book/Market Q5	0.292	[4.52] ***	0.202	[2.52] **	0.495	[5.03] ***	0.316	[4.82] ***	-0.082	[-0.71]	0.320	[4.05] ***
Bond Characteristic Controls												
Bond Coupon Rate	0.028	[1.68] *	-0.018	[-0.27]	0.093	[1.31]	0.058	[1.10]	-0.203	[-1.71] *	0.050	[0.81]
Bond Yield	0.102	[2.48] **	0.333	[4.46] ***	0.206	[2.88] ***	0.448	[6.32] ***	-0.252	[-1.54]	0.433	[6.11] ***
Bond Credit Spread	-0.034	[-1.09]	0.075	[1.00]	0.137	[1.78] *	0.031	[0.46]	-0.054	[-0.41]	0.046	[0.69]
Bond Value	0.000	[0.21]	0.006	[0.09]	0.060	[1.48]	-0.060	[-1.27]	-0.037	[-0.50]	-0.070	[-1.43]
Bond Age	0.005	[1.19]	-0.050	[-1.07]	0.015	[0.33]	0.001	[0.03]	0.154	[1.95] *	0.006	[0.14]
Bond Maturity	0.006	[0.85]	0.226	[0.97]	0.025	[0.11]	0.061	[0.32]	0.482	[1.25]	0.110	[0.61]
Bond Duration	-0.009	[-0.42]	-0.072	[-0.36]	0.174	[0.79]	0.099	[0.57]	-0.207	[-0.51]	0.108	[0.64]
Bond Bid/Ask Spread	0.059	[2.42] **	0.038	[1.10]	0.002	[0.06]	0.065	[1.72] *	-0.147	[-2.47] **	0.070	[1.83] *
Bond Reversal	-0.010	[-1.50]	0.059	[1.55]	0.028	[0.71]	-0.020	[-0.54]	0.068	[0.97]	-0.029	[-0.78]
Bond Momentum	-0.004	[-0.76]	-0.072	[-1.39]	-0.050	[-1.10]	-0.014	[-0.35]	0.144	[1.24]	-0.026	[-0.58]
Bond Rating	-0.034	[-3.56] ***	-0.011	[-0.10]	-0.073	[-0.67]	-0.189	[-2.48] **	-0.334	[-1.26]	-0.219	[-2.61] ***
Nearness to Default	0.011	[1.68] *	-0.084	[-1.05]	-0.093	[-1.08]	0.029	[0.36]	0.458	[1.58]	0.041	[0.54]
Stock Characteristic Controls												
Beta	-0.011	[-0.29]	0.105	[1.33]	0.093	[1.27]	0.056	[0.78]	-0.145	[-0.45]	0.028	[0.37]
Market Capitalization	0.002	[0.14]	0.109	[1.31]	0.082	[1.05]	0.029	[0.47]	0.054	[0.21]	0.038	[0.54]
Book/Market	-0.041	[-1.79] *	-0.026	[-0.30]	-0.084	[-1.03]	-0.003	[-0.04]	-0.016	[-0.06]	-0.003	[-0.04]
Short-term Reversal	0.012	[6.15] ***	0.260	[3.45] ***	0.269	[3.50] ***	0.347	[5.14] ***	-0.498	[-2.08] **	0.281	[4.42] ***
Momentum	0.001	[2.26] **	0.108	[1.33]	0.113	[1.37]	0.092	[1.63]	-0.511	[-1.61]	-0.004	[-0.06]
Long-term Reversal	0.000	[-0.97]	-0.179	[-2.48] **	-0.081	[-1.27]	0.045	[0.80]	-0.097	[-0.39]	-0.011	[-0.19]
Accruals	0.027	[0.75]	-0.026	[-0.39]	-0.006	[-0.08]	-0.042	[-0.75]	-0.195	[-1.04]	-0.068	[-1.20]
SUE	0.250	[0.62]	-0.020	[-0.38]	-0.016	[-0.29]	0.128	[2.14] **	-0.129	[-0.64]	0.126	[2.40] **
Gross Profitability	-0.138	[-1.73] *	0.167	[1.48]	0.157	[1.60]	0.145	[1.90] *	0.224	[0.71]	0.186	[2.39] **
Earnings Yield	0.246	[1.35]	0.048	[0.71]	-0.010	[-0.18]	0.083	[1.25]	-0.203	[-0.96]	0.045	[0.67]
Market Microstructure Controls												
Number of Bonds in *t*+1	0.000	[-2.10] **	0.000	[-0.68]	0.000	[-0.27]	0.000	[-0.60]	0.000	[-0.40]	0.000	[-1.12]
Percent of Bond Market Cap Traded in *t*+1	-0.151	[-1.80] *	-0.124	[-0.87]	-0.199	[-1.39]	-0.145	[-1.48]	-0.286	[-0.83]	-0.186	[-1.83] *
Number of Days from Beginning of Month *t*+1	0.004	[1.35]	-0.003	[-1.05]	-0.001	[-0.32]	0.001	[0.20]	-0.003	[-0.62]	0.001	[0.31]
Number of Days from End of Month *t*+1	0.012	[3.35] ***	-0.003	[-0.86]	0.000	[0.05]	0.011	[3.20] ***	0.000	[0.02]	0.010	[3.03] ***
Intercept	0.269	[1.10]	0.083	[0.19]	-1.290	[-0.88]	-0.560	[-1.25]	2.417	[2.22] **	-0.239	[-0.55]
Observations	1,139		664		838		1,149		1,169		1,149	
Adj. R-Squared	0.31		0.53		0.53		0.26		0.58		0.28	
Industry Control	Yes		Yes		Yes		Yes		Yes		Yes	

Table 4: Factor Model Time Series Regressions

The table shows results from time series regressions of monthly portfolio returns (in excess of 1-month USD LIBOR) on bond factor models. Bonds are sorted each month into quintiles based on bond book-to-market (BBM) and combined into equal-weighted or value-weighted portfolios. The table reports intercepts, slope coefficients, *t*-statistics, the number of observations, and R-squared separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the return spreads between the highest bond book-to-market (Q5) and lowest bond book-to-market (Q1) quintiles. Regressors for the BBW (2019) factor model in Panel A are the excess return on the bond market portfolio, return spreads based on value-at-risk (the second worst returns in the previous 3 years), rating (credit rating), illiquidity (the Roll measure), and reversal (past one-month return). The Augmented BBW factor model in Panel B further adds a term structure factor, constructed from independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. The difference in returns between these two extreme maturity quintiles is our term structure factor. Panel C shows intercepts of equal-weighted portfolios for the BBW factor model and the augmented BBW factor model separately for small and large bonds (from sequential sorts on BBM and size based on the median monthly bond value). In addition, it shows results using a 21-factor model consisting of 13 equity and eight bond factors. The equity market factors include all five equity factors of Fama and French (2015); 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 issuers 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. 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.

(continued)

Table 4: Factor Model Time Series Regressions (continued)

Panel A: BBW Factor Model

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

(continued)

Table 4: Factor Model Time Series Regressions (continued)

Panel B: Augmented BBW Factor Model

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

(continued)

Table 4: Factor Model Time Series Regressions (continued)

Panel C: Robustness

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

Table 5: Default Risk and Liquidity Interactions

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

(continued)

Table 5: Default Risk and Liquidity Interactions (continued)

Panel A: Default Risk

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

(continued)

Table 5: Default Risk and Liquidity Interactions (continued)

Panel B: Liquidity

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

Table 6: Treasury Bonds

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

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

(continued)

Table 6: Treasury Bonds (continued)

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

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

The table shows results from time series regressions of monthly portfolio returns (in excess of 1-month USD LIBOR) on bond factor models augmented with a high-minus-low factor based on bond book-to-market (BHML). Bonds are sorted each month into quintiles based on bond book-to-market and combined into equal-weighted portfolios. The table reports intercepts, slope coefficients, t-statistics, the number of observations, and R-squared separately for each of the five portfolios (Q1, Q2, Q3, Q4, Q5), and for the corresponding times-series of return spreads between the highest book-to-market (Q5) and lowest book-to-market (Q1) bond quintiles. To form the Bond HML factor, each month, we divide bonds into one of 6 categories based on bond size (market value outstanding) and bond book-to-market. For the 3 categories in the larger of the two bond sizes (bottom, middle, and top third of month-t bond book-to-market), we compute the spread in the month $t+1$ value-weighted bond returns (based on bond value outstanding) between the top and bottom third bond book-to-market bonds. We then repeat the exercise for the bonds in the smaller of the two bond sizes. We then average the two value-weighted return spreads and include the average as the 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, constructed from independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. The difference in returns between these two extreme maturity quintiles is our term structure factor. 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. Bond mispricing measures deviations of a firm's aggregate debt obligations from predictions based on its accounting variables. Each month *t*, we cross-sectionally regress $V_{i,t}$ on firm *i*'s 28 most commonly reported items from Compustat's point-in-time accounting database. The regression predictions represent month *t* peer-implied norms for each firm's total liabilities. Each bond is then assigned the BG signal of its issuing firm, which is the percentage deviation of the firm's predicted $V_{i,t}$ from its actual value. Across different specifications, returns are regressed against prior month values for bond book-to-market, bond mispricing, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. The table employs quintile dummies for the characteristics as regressors. Each month's quintiles are determined from sorts of bonds with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for quintiles 2, 3, 4, and 5 of each characteristic but the table displays only the coefficients of the quintile dummy with the largest amount of the characteristic (Q5) on bond book-to-market and bond mispricing for brevity. Additional controls are the number of outstanding bonds of a firm, the percentage of bond market capitalization of a firm that trade in a month, and the number of days from the beginning and end of the month of bond price data used to calculate the bond return. All regressions include industry dummy variables based on the 38 Fama and French industry classifications. The table shows average coefficients and test statistics as well as the average number of observations and average adjusted R-Squared. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. 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 Panel A. Across different specifications, returns are regressed against prior month values for bond book-to-market, bond coupon rate, bond yield to maturity, bond credit spread, bond value, bond age, bond maturity, bond duration, bond bid-ask spreads, lagged bond returns, bond momentum, bond credit rating, nearness to default, equity market beta, equity book-to-market, equity market capitalization, equity short-term reversal, equity momentum, equity long-term reversal, accruals, standardized unexpected earnings surprise (SUE), gross profitability, and earnings yield. 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 bonds with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. The regressions include dummy variables for quintiles 2, 3, 4, and 5 of each characteristic, but the 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, constructed from independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. The difference in returns between these two extreme maturity quintiles is our term structure factor. 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. 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, constructed from independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. The difference in returns between these two extreme maturity quintiles is our term structure factor. To form the Bond HML factor, each month, we divide bonds into one of 6 categories based on bond size (market value outstanding) and bond book-to-market. For the 3 categories in the larger of the two bond sizes (bottom, middle, and top third of month-t bond book-to-market), we compute the spread in the month $t + 1$ value-weighted bond returns (based on bond market capitalization) between the top and bottom third bond book-to-market bonds. We then repeat the exercise for the bonds in the smaller of the two bond sizes. We then average the two value-weighted return spreads and include the average as the Bond HML factor. 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. 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 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 employs the normal score of bond book-to-market. Each month's quintiles are determined from sorts of bonds with non-missing values for all characteristics. Size (market capitalization) quintiles are based on NYSE breakpoints. 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, constructed from independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. The difference in returns between these two extreme maturity quintiles is our term structure factor. 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. 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, constructed from independent triple sorts of bonds into 125 face value-weighted portfolios based on maturity, coupon and credit rating. We take the simple average of returns across the 25 portfolios of the top 20% of bonds in terms of maturity for the long position, and do the same for the bottom 20%. The difference in returns between these two extreme maturity quintiles is our term structure factor. The second column reports one-way turnover (in percent per month). Columns 3-6 report the average transaction costs based on two-way turnover and transaction cost adjusted (net) performance as the intercept of a regression of quintile portfolio returns (in excess of 1-month USD LIBOR) minus monthly transaction costs on the risk factors. Standard errors are estimated using the Newey West (1987) procedure. Daily average bid and ask prices are computed by taking the average of all dealer buy and dealer sell transactions for all bonds in a quintile. We then take the average of daily bids and asks in a month separately for bids and asks, and compute monthly bid-ask spreads. We assign these quintile-level half spreads to bonds that join the quintile, and calculate transaction costs as in Eq. (4). As shown in the column headings, the bid-ask spreads are calculated alternatively for all transactions in TRACE (All) and transactions with volume at least 100,000 U.S. dollars (Institutions). The return sample period is February 2003 to September 2020.

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

Internet Appendix A: Variable Definitions

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

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

(continued)

Internet Appendix A: Variable Definitions (continued)

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