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Are Capital Market Anomalies Common to Equity and Corporate Bond Markets? An Empirical Investigation

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Abstract

Corporate bond returns exhibit predictability in a manner consistent with efficient pricing. Many equity characteristics, such as accruals, standardized unexpected earnings, and idiosyncratic volatility, do not impact bond returns. Profitability and asset growth are negatively related to corporate bond returns. Because firms that are profitable or have high asset growth (and hence more collateral) should be less risky, with lower required returns, the evidence accords with the risk–reward paradigm. Past equity returns are positively related to bond returns, indicating that equities lead bonds. Cross-sectional bond return predictors generally do not provide materially high Sharpe ratios after accounting for trading costs.

I. Introduction

Firms finance their assets using a mixture of debt and equity claims, and debt financing is a material part of capital structure. Indeed, according to Graham, Leary, and Roberts (2015), the average debt-to-assets ratio for U.S. corporations (excluding financial, utility, and railroad firms) amounted to as much as 35% in 2010. It is thus important to understand the cross section of returns in both sets

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of markets. A voluminous body of work describes financial statement items and other characteristics that predict equity returns (Kothari (2001)). In this article, we instead focus on the debt (corporate bond) market and seek to answer the following questions: Do corporate bond returns exhibit return predictability similar to that in equities? If so, are the predictors consistent with risk pricing, frictions, or behavioral biases? And does the magnitude of return predictability in corporate bonds permit arbitrage profits beyond transaction cost bounds?

Although it stands to reason that corporate bonds are not as sensitive to firm outcomes as equities, corporate bond return volatility is still material, at about a third of that of equities for junk bonds and about a fifth for investment-grade bonds (Acharya, Amihud, and Bharath (2013), Campbell, Lettau, Malkiel, and Xu (2001)). Our premise is that cash flow uncertainty caused by credit risk could have commonalities with equities, and the risk-based factors and possible investor biases that apply in equity markets might also, therefore, apply to the credit risk sector. We perform our analysis using an extensive panel of corporate bonds from 1973 to 2014. Our data are assembled from 4 distinct data sets, namely, the Lehman Brothers Fixed Income Database, the Trade Reporting and Compliance Engine (TRACE), the Mergent Fixed Income Securities Database/National Association of Insurance Commissioners (FISD/NAIC), and Datastream. We work with returns on corporate bonds in excess of returns on the Treasury bonds with the same cash flow schedule as the corporate bonds. This allows us to focus on the cross section of corporate bonds while abstracting from interactions of bond returns with Treasury yields.

Within the equity market, the literature has attributed the predictive ability of various characteristics to risk, frictions, or behavioral biases of investors. Thus, the book-to-market effect has been attributed to distress risk by Fama and French (1993). Return predictors linked to asset growth (Cooper, Gulen, and Schill (2008), Fairfield, Whisenant, and Yohn (2003)) and profitability (Fama and French (2008)) have been rationalized within the risk–reward (RR) paradigm, in the context of the q-theory of the firm (Hou, Xue, and Zhang (2015)). Short-horizon (monthly and weekly reversals documented by Jegadeesh (1990) and Lehmann (1990)) have been attributed to frictions such as illiquidity (Jegadeesh and Titman (1995), Nagel (2012)). Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011) attribute the ability of accruals (Sloan (1996), Lev and Nissim (2006)) and standardized unexpected earnings (Bernard and Thomas (1989), (1990)) to predict returns to limited attention. Momentum over 3- to 12-month horizons (Jegadeesh and Titman (1993)) has been motivated by overconfidence and self-attribution (Daniel, Hirshleifer, and Subrahmanyam (1998)) as well as the conservatism bias and the representativeness heuristic (Barberis, Shleifer, and Vishny (1998)). The idiosyncratic volatility (IVOL) anomaly (Ang, Hodrick, Xing, and Zhang (2006)) has also been attributed to investor misreaction in the work of Stambaugh, Yu, and Yuan (2015).[1]

[1]Conversely, Bali, Cakici, and Whitelaw (2011) and Conrad, Kapadia, and Xing (2014) show that the IVOL effect disappears upon controlling for demand for lottery-like payoffs, whereas Bali and Cakici (2008) and Han and Lesmond (2011) provide evidence that the IVOL effect occurs due to liquidity shocks and microstructure effects. In fact, Bali and Cakici show that data choices have an impact on the robustness of the IVOL effect. Mashruwalla, Rajgopal, and Shevlin (2006) and

We analyze whether the preceding equity return characteristics also impact bond returns, and we attempt to discern the underlying causes of cross-sectional return predictability in corporate bonds. There is a rich literature examining the link between stock and bond returns. Collin-Dufresne, Goldstein, and Martin (2001) find that changes in default probabilities and in recovery rates have modest explanatory power for changes in credit spreads. Schaefer and Strebulaev (2008) show that while the Merton (1974) model hedge ratios match empirically observed stock–bond elasticities, the structural models of credit risk are poor predictors of bond prices.[2] The goal of our article, then, is to identify whether bond returns can in fact be explained by the variables that go beyond standard credit measures (i.e., those that capture stock return anomalies). In other words, we explore whether predictability arising from these characteristics is what leads to the failure of structural models of bond prices.

We present results from Fama–MacBeth (1973) regressions of excess bond returns on lagged equity characteristics and from long–short hedge portfolio returns. We control for a number of bond characteristics, including past bond returns, distance to default (DD) (Merton (1974)), issue size, maturity, ratings along with leverage, and the Amihud (2002) illiquidity measure. The robust results across these regressions are that profitability, asset growth, lagged bond and equity returns, illiquidity, and credit ratings impact the cross section of corporate bond return spreads, but other equity characteristics such as accruals, earnings surprises, and idiosyncratic volatility do not. The economic significance of the predictability is higher for junk bonds than it is for investment-grade bonds. However, the signs of forecasting regressions for some variables are the opposite of the corresponding ones for equities. The sign of the coefficient on the 1-month lagged equity return is positive (although the sign on the corresponding 1-month lagged bond return is negative), and the sign of the coefficient on profitability is negative.

The positive sign on the 1-month lagged equity return is consistent with the notion that stocks lead bonds in reflecting information. The negative sign on asset growth has been rationalized by Hou et al. (2015) in the context of the q-theory of the firm. The idea is that firms are likely to invest more if the expected return on equity (and bonds) is sufficiently low. Also, higher asset growth will provide more collateral to bondholders, thus reducing bond spreads. With regard to profitability, if the debt of more profitable firms is safer, it will command lower expected returns, which is what we find.

We also investigate whether the magnitude and significance of the anomalies vary with investor sentiment. Stambaugh, Yu, and Yuan (2012) show that the profitability does vary with sentiment and attribute it to overvaluation in

Green, Hand, and Soliman (2011) argue that increased arbitrage has led to a decrease in the profitability of the accruals anomaly (see also Khan (2008), Richardson, Tuna, and Wysocki (2010), and Ball, Gerakos, Linnainmaa, and Nikolaev (2016)). Schwert (2003), Chordia, Subrahmanyam, and Tong (2014), and McLean and Pontiff (2016) examine the profitability of anomalies over time.

[2]Bao and Hou (2013) also find that the empirical patterns in the comovements of short-term and long-term bonds with equities are consistent with the Merton (1974) model. Kapadia and Pu (2012) suggest that this failure of credit risk models is due to a lack of integration between the stock and bond markets caused by limits to arbitrage and illiquidity.

high-sentiment periods due to investor optimism. We find that aside from the asset growth anomaly, none of the anomalies conditionally varies with sentiment, indicating that they do not arise due to irrational optimism, as posited by Stambaugh et al. (2012) for the equity market. Even the asset growth effect in the bond market is not robust to transaction cost considerations, as we discuss later.

We next control for systematic risk by regressing hedge portfolio returns on the Fama–French (2015) factors (market, equity market capitalization, value, investment, and profitability factors), the Pástor and Stambaugh (2003) liquidity factor, and 2 bond market factors based on the term structure slope and credit spreads.[3] After risk adjustment, we find that the alphas of most of the hedge portfolios attenuate but remain significant.

Because transaction costs are substantial in bond markets, we examine the impact of these costs on the economic significance of the portfolio alphas. We use two different estimates of transaction costs: i) trading costs estimated from an econometric model by Edwards, Harris, and Piwowar (2007), and ii) following Bao, Pan, and Wang (2011), we use the Roll (1984) measure of effective spreads calculated from autocovariances of bond returns. We find that only portfolios formed by sorting on bond ratings provide significantly positive returns net of both measures of transactions costs. Because the Edwards et al. transaction cost measures are lower, hedge portfolios formed by sorting on past equity and bond returns, profitability, investment, and illiquidity also provide significant positive net returns measured as per Edwards et al. (2007). However, Bao et al. (p. 913) argue that the Edwards et al. measure may be biased downward because it "does not fully capture many important aspects of liquidity such as market depth and resilience." On the basis of this argument, our results indicate that anomaly-based returns in corporate bonds do not survive transaction costs. In other words, the challenges in earning arbitrage profits in the illiquid corporate bond market significantly attenuate anomaly-based profits.

Because our results survive standard risk controls, it is possible that the standard factors might miss priced sources of risks in bond markets. Therefore, we investigate whether the magnitudes of the Sharpe (1966) ratios obtained from hedge portfolio returns and alphas accord with risk-based arguments. We do this by statistically comparing the Sharpe ratios to a threshold suggested by MacKinlay (1995), below which the ratio accords with missing risk factors. None of the ratios net of transaction costs is statistically higher than the threshold. Thus, overall, bond markets are largely efficient net of transaction costs and possibly an omitted risk factor.

Many authors (e.g., Stoll (1978), Grossman and Miller (1988), and Conrad, Gultekin, and Kaul (1997)) indicate that monthly return reversals (Jegadeesh (1990)) arise because inventory concerns cause liquidity providers to demand compensation. Thus, an excess selling pressure, for example, causes market makers to lower the price to earn a risk premium for absorbing the inventory. We do

[3]For our extended sample period, bond liquidity measures are not readily available because we do not have data at greater than a monthly frequency for part of the sample. However, because bond and stock liquidity levels are positively correlated (Maslar (2013)), the Pástor and Stambaugh (2003) stock liquidity factor potentially also applies in the bond market.

indeed find evidence of reversals in the corporate bond market. We find that the hedge portfolio profits based on monthly reversals are significantly related to the Hu, Pan, and Wang (2013) noise measure as a proxy for bond illiquidity. This supports the notion that monthly reversals represent compensation for liquidity provision.

In the two articles most closely related to ours, Gebhardt, Hvidkjaer, and Swaminathan (2005a), (2005b) also consider the cross section of expected bond returns. The major differences between their work and ours are that we use more extensive data (they use the Lehman Brothers data from 1973 to 1996) and we explicitly consider whether stock-market-based anomaly variables play a role in corporate bond markets. Further, our methodology focuses more on ascertaining whether the stock-related characteristics influence corporate bond returns after accounting for risk adjustment and whether the signs and magnitudes of these influences accord with risk-based pricing. Like Gebhardt et al. (2005b), we also find a strong influence of past stock returns on future bond returns. However, we are able to show that stock characteristics matter for corporate bond returns beyond the influence of stock momentum. Another related article is that by Jostova, Nikolova, Philipov, and Stahel (2013), who show, using data similar to ours, that there is significant momentum in corporate bond returns even after accounting for exposures to systematic risks or transaction costs. We find that there is indeed a cross-momentum effect from equity returns to bond returns in our sample. Further, in our multivariate analysis, we find that cross-momentum from equities dominates own-momentum in corporate bond returns in excess of that on matching Treasury bonds (although there is momentum in gross corporate bond returns, confirming Jostova et al.'s findings). Finally, Bai, Bali, and Wen (2014) analyze the relation between bond return moments and bond returns.

In a closely related and contemporaneous paper, Choi and Kim (2016) consider the impact of 6 anomalies on the cross section of corporate bond returns. Among other results, they find that asset growth is negatively related to corporate bond returns but that profitability is not significant. In contrast, within our sample, although asset growth does predict corporate bond returns, profitability is negatively priced; in addition, we document a strong lead from monthly equity returns to monthly bond returns.[4]

In addition, our article is linked to work that analyzes the pricing implications of credit risk on equities. Vassalou and Xing (2004) construct a credit risk measure based on DD, and Campbell, Hilscher, and Szilagyi (2008) construct bankruptcy indicators to forecast stock returns. Anginer and Yildizhan (2013) find that the credit spreads of corporate bonds explain cross-sectional variations in the equity risk premium, and Friewald, Wagner, and Zechner (2014) find that credit risk premia implied by credit default swap (CDS) spreads are priced

[4]Choi and Kim (2016) use the Reuters Fixed Income Database and the Lehman Brothers Fixed Income Database for their sample spanning 1979–2012. We use 4 data sets to construct a sample spanning the period 1973–2014. Also see Crawford, Perotti, Price, and Skousen (2015), who analyze accounting-based variables to predict bond returns using Datastream and TRACE data from 2001 to 2011.

in equity markets. We complement these studies by instead linking bond returns to firm characteristics.[5]

II. Corporate Bond Data and Bond Returns

A. Data

We obtain prices of senior unsecured corporate bonds from the following 4 data sources: i) For 1973–1997, we use the Lehman Brothers Fixed Income Database which provides month-end bid prices. Although the prices in the Lehman Brothers Fixed Income Database are quote based, they are considered to be reliable (Hong and Warga (2000)). Some observations are dealers' quotes, whereas others are matrix prices. Matrix prices are set using algorithms based on the quoted prices of other bonds with similar characteristics. Although matrix prices are less reliable than dealer quotes (Warga and Welch (1993)), we include these prices because they could increase the power of our tests.[6] ii) For 1994–2011, we use the Mergent FISD/NAIC data. This database consists of actual transaction prices reported by insurance companies. iii) For 2002–2014, we use the TRACE data, which also provide transaction prices. The observations from the transaction-based data from Mergent FISD/NAIC and TRACE are not always on the last trading day of a month. We use only the last observation during the final 5 trading days of each month; if there is no observation during these 5 days, the price is set to be missing. iv) Finally, we obtain month-end quotes from 1990 to 2011 from the Datastream database.

We apply the following filters: i) Prices that are less than 1 cent per dollar or more than the prices of matching Treasury bonds are removed; ii) if prices appear to bounce back in an extreme fashion relative to preceding days, they are excluded; specifically, denoting R_t as the date t return, we delete a date t observation if $R_t R_{t-k} < -0.02$ for $k = 1, \ldots, 12$; and iii) prices that do not change for more than 3 months are excluded. These filters reduce our sample sizes by 9.5%, 1.3%, and 7.2%, respectively.

We calculate a return in month t only if we have valid prices in month t and $t-1$. This means that we do not impute a return (of 0 or index return) for missing months. Therefore, if we do not have a return for a bond in month t, it is not included in the analysis for that month. A bond-month is also not included in any regression analysis that includes returns over multiple lags if any of the lagged returns are missing. Furthermore, unlike Bessembinder, Kahle, Maxwell, and Xu (2009), we desist from dropping trades below $100,000 because our focus is not so much a corporate event study as studying the cross section of bond returns. Our not imposing a filter on bond trade size is consistent with not imposing a filter in studies of the cross section of equity returns. In unreported results, however, we find that there is virtually no difference to our main results if we do impose this filter.

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[5]Other articles linking credit and equity markets include those by Lin, Wang, and Wu (2011) and Koijen, Lustig, and Nieuwerburgh (2017). Generally, although these papers provide important insights, they either look at CDS markets (which do not span all corporate bonds) or consider subsets of our variables.

[6]In Appendix Table A2, we show that our results are robust to the exclusion of matrix prices.

Because our data come from different sources, we check for differences/similarities across the various databases. Table A1 in the Appendix shows that the Datastream sample has higher returns and higher autocorrelations in bond excess returns than those in the other data sets. We also find that there are many missing values in Datastream, and the prices often do not change for more than several months. Appendix Table A2 shows that our main results are robust to the exclusion of Datastream data from our sample.

Given that there are overlapping observations across the databases, we prioritize in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and Datastream. As Jostova et al. (2013) find, the degree of overlap is modest at less than 6% across all the data sets. To check data consistency, we examine the effect of our ordering by reversing the priority. We show in Appendix Table A2 that our main empirical findings are not sensitive to our ordering choice.

The Lehman Brothers Fixed Income Database and Mergent FISD/NAIC provide other characteristics specific to the issuer of bonds, such as the maturity dates, credit ratings, coupon rates, and optionalities of the bonds. We remove bonds with floating rates and with any option features other than callable bonds. Until the late 1980s, there are very few bonds that are noncallable. Thus, removing callable bonds reduces the length of the sample period significantly; therefore, we include these bonds in our sample. Because the callable bond price reflects the discount due to the call option, the return on these bonds may behave differently from the return on noncallable bonds. We address this concern by adding fixed effects for callable bonds, and we show in Appendix Table A2 that our results remain robust.

We merge all four bond databases using the Committee on Uniform Securities Identification Procedures (CUSIP) identifiers at both the firm and issue levels. Because CUSIP identifiers vary over time, we also use the historical CUSIP of the Center for Research in Security Prices (CRSP) and the RatingsXpress of Compustat to match issuers and issues. Finally, we manually match remaining issuers based on the ticker information provided by Bloomberg's data point (BDP) function.

After matching the equity and accounting information (data described later) to the bond observations, we have an unbalanced panel of around 925,000 bond-month return observations with 18,850 bonds issued by 3,588 firms over 504 months. Our sample size is smaller than that of Jostova et al. (2013) because we only use observations of listed firms that can be matched to both equity returns and accounting information. In the analysis to follow, we perform two types of regressions. The first type uses all available bonds. The second type, a robustness check, uses 1 bond per firm. For this second category, we require at least 50 firms per month to run our regressions. After applying our filtering criteria, because of irregularities in Mergent FISD/NAIC and Datastream, we omit the period from May 1998 to Mar. 2001 for the robustness check, during which we do not have enough firms in our sample to run the regressions reliably.

B. Bond Returns

The monthly return on corporate bond i, R^b_{it}, is constructed inclusive of the accrued interest and the coupon, that is, $R^b_{it} \equiv (P_{it} + I_{it} + C_{it})/(P_{it-1} + I_{it-1}) - 1$, where P_{it} is the price of corporate bond i at time t, I_{it} is the accrued interest, and C_{it} is the paid coupon. To ensure that we do not pick up variations in bond returns due to movements in default-free bond prices, we need to account for variation in the risk-free return. We thus compute an "excess return" on corporate bonds as follows.

We construct the return on a *synthetic* Treasury bond (denoted R_{it}^{f}) that has the same coupon rate and the repayment schedule as the ith corporate bond in a manner analogous to that for the corporate bond. To obtain the price of the synthetic bond, we interpolate the Treasury (par) yield curve (data from the Federal Reserve Board) using cubic splines and construct zero coupon curves for Treasuries by bootstrapping. Each month, for each corporate bond in the data set, we construct the future cash flow schedule from the coupon and principal payments. We then multiply each cash flow with the zero-coupon Treasury bond price with the corresponding time to maturity. We match the maturity of the zero-coupon Treasury prices to the cash flow exactly by linearly interpolating continuously compounded forward rates from the on-the-run yield curve. We add all the discounted cash flows to obtain the synthetic Treasury bond price whose cash flows match those of the corporate bond. These prices, and the corresponding accrued interest and coupon, are used to construct R_{it}^{f}. The excess bond return that we use for our analysis is $R_{it} \equiv R_{it}^{b} - R_{it}^{f}$.

It is possible to calculate excess bond returns using other methods. Thus, one can use a maturity-matched Treasury bond or a duration-matched Treasury bond to compute a credit spread or an excess return. These methods have the virtue of being simpler to implement. But using a maturity-matched Treasury bond can cause excess returns to move mechanically as a result of shocks to Treasury yield curves because coupon rates, in general, differ across corporate and Treasury bonds. If we use a duration-matched Treasury bond, the excess return will be immune to a parallel shift in a Treasury yield curve but will be affected by a change in the slope or the curvature of the yield curve. Our measure of the excess return on a corporate bond is less directly affected by any change in the Treasury yield curve. Note, however, that cash flow matching is still not perfect for a corporate bond that is close to default because the cash flow of such a bond is likely to be accelerated rather than paid as scheduled. On balance, we choose to adopt our cash-flow-matching procedure for adjusting raw corporate bond returns.

C. Descriptive Statistics

Table 1 presents the summary statistics of excess returns on corporate bonds. The table shows the aggregate statistics and the breakdown based on credit ratings. The corporate bonds are classified either as investment grade (IG) or as non-investment grade (junk). Within IG, there are AAA/AA-rated (denoted AA+), A-rated, and BBB-rated bonds.

Panel A of Table 1 shows the distributions of the excess returns on the corporate bonds for each category. The mean monthly excess return is 0.11% for all bonds, and it decreases monotonically with the bond rating. IG bonds earn lower excess returns than junk bonds. Returns on junk bonds are more volatile than IG bond returns, as evidenced by their higher standard deviation. The first-order autocorrelation (AR1) is generally negative. Further, the sum of

TABLE 1

Summary Statistics on Bond Returns and Characteristics

Table 1 presents summary statistics for all bonds used in the article. Bonds are also divided into investment-grade (IG) and junk categories. IG bonds are further subdivided into AA+, A, and BBB categories. Excess return is calculated in excess of the matching Treasury bond that has the same coupons and repayment schedule. AR1–AR3 are the autocorrelation coefficients at lags 1–3, and AR1–AR6 is the sum of the first 6 autocorrelation coefficients. No Price Change is the number of observations with no price change from the previous month. % Market Value is the time-series average of the ratio of the market value of bonds in a specific rating category to the total market value of all bonds. MAT is the average time to maturity in years. Corr is the correlation between excess returns on a corporate bond and stock returns; this correlation is calculated using the entire panel of observations in a rating category. % Issuers Equity Size is the ratio of issuers whose market value of equity is below the 20th percentile market cap for Micro, between the 20th and 50th percentiles for Small, and above the 50th percentile market cap for Big (the percentiles are calculated using only New York Stock Exchange (NYSE) stocks). The sample period is 1973–2014.

Panel A. Excess Returns

Category	Mean	Std. Dev.	Median	AR1	AR2	AR3	AR1–AR6
All	0.11	2.93	0.10	−0.13	−0.04	0.10	−0.11
IG	0.06	2.38	0.06	−0.24	−0.07	0.12	−0.23
AA+	0.01	2.25	0.03	−0.29	−0.12	0.16	−0.29
A	0.05	2.33	0.04	−0.26	−0.08	0.12	−0.25
BBB	0.10	2.49	0.10	−0.20	−0.04	0.10	−0.18
Junk	0.26	4.24	0.28	−0.01	0.00	0.05	0.02

Panel B. Characteristics

						% Issuers Equity Size		
Category	*N*	No Price Change	% Market Value	MAT	Corr	Micro	Small	Big
All	924,859	16,912	100.0	12.2	0.2	6.0	13.6	80.3
IG	726,163	8,042	76.7	13.3	0.2	1.1	8.1	90.7
AA+	134,855	2,790	13.4	15.6	0.3	0.8	7.5	91.7
A	306,228	3,410	32.1	13.6	0.2	0.9	7.7	91.3
BBB	285,080	1,842	31.2	11.7	0.2	1.5	8.9	89.6
Junk	190,631	8,485	22.2	8.7	0.2	20.1	30.5	49.4

the first 6 autocorrelations increases monotonically with ratings, from −0.29 for AA+ bonds to 0.02 for junk bonds. The consistently negative AR1 coefficient suggests monthly reversals. We will test this more formally in a multivariate setting.

Panel B of Table 1 shows various characteristics of bonds and their issuers. The total number of bond-month observations is 924,859 including 8,064 for non-rated bonds. Because there are more IG bonds outstanding and they are more frequently traded, we have more observations on such bonds (726,163 or 79.21% of the total number of observations) relative to junk bonds (190,631 or 20.79% of the total number of observations). The number of observations with zero price change is a measure of bond liquidity. Overall, only 1.8% of observations are associated with no price changes. This low proportion shows that the corporate bond prices in our sample are fairly variable and likely to be informative about the link between bonds and equities.

IG bonds constitute a larger fraction of the total market value (76.7% of the total bond market capitalization in our sample) than junk bonds (22.2%). This means that value-weighted bond portfolios, which we study later in the paper, are likely to be more representative of IG bonds than equal-weighted ones. However, because the ratio of the number of observations across the two categories is not very different from the ratio of the market values, the difference between equal- and value-weighted portfolios may be that limited (unlike the case for micro-cap and large stocks noted by Fama and French (2008)). Time to maturity (MAT) differs little across rating categories, although junk bonds tend to have shorter maturities, possibly because investors are reluctant to lend long term to firms with higher credit risk. The overall correlation between equity returns and bond excess returns is modest at 0.2 for the entire sample, which is consistent with Collin-Dufresne et al. (2001).

We also consider characteristics of the issuers of bonds. We classify issuers as micro if their market capitalization is below the 20th percentile, small if their capitalization is between the 20th and 50th percentiles, and big if their capitalization is above the 50th percentile (the percentiles are calculated using New York Stock Exchange (NYSE) breakpoints). In our sample, 80.3% of observations are of big firms, 13.6% of small firms, and only 6.0% of micro-cap firms. Our bond sample is, thus, different from the equity sample of Fama and French (2008), who report that 1,831 firms out of a total of 3,060 correspond to micro stocks, and only 626 firms correspond to big stocks (using the 20th and 50th percentile breakpoints for NYSE firms' equity market capitalizations). They also find that some return predictors (e.g., asset growth and profitability) work only for micro stocks and have weak or no predictability for big stocks. This observation leads to a caveat in our study; namely, that some equity return predictors may not forecast bond returns simply because corporate bonds are issued mostly by big firms in our sample.

III. Bond Return Predictors

Our sample consists of all publicly traded firms with a bond issue.[7] We obtain equity returns from CRSP and accounting information from Compustat. All accounting variables are assumed to become available 6 months after the fiscal year-end, whereas market-related variables (returns and prices) are assumed to be known immediately. We construct the following equity return predictors:

i) Size (ln(MC)): the natural logarithm of the market value of the equity of the firm (in millions of dollars) (Banz (1981), Fama and French (1992)).

ii) Value (ln(BM)): the natural logarithm of the ratio of the book value of equity to the market value of equity. The book value is calculated as in Fama and French (2008).

iii) Momentum (REQ26): the cumulative 5-month return on equity skipping the most recent month (Jegadeesh and Titman (1993)).

iv) Past month's equity return (REQ1): the stock's return, lagged 1 month (Jegadeesh (1990)).

v) Accruals (ACCRU): the ratio of accruals to assets, where accruals are defined as the change in (current assets − cash and short-term investments − current liabilities + short-term debt + taxes payable) less depreciation (Sloan (1996)).

[7]Although we include financial firms in our sample for completeness (unlike, e.g., Fama and French (1992)), our results are virtually unchanged when we exclude them from the analysis.

vi) Asset growth (ASTG): the percentage change in total assets (Cooper et al. (2008)).

vii) Profitability (PROF): the ratio of equity income (income before extraordinary items − dividend on preferred shares + deferred taxes) to book equity (Fama and French (2008)).[8]

viii) Net stock issues (NETISS): the change in the natural log of the split-adjusted shares outstanding (see Pontiff and Woodgate (2008), Fama and French (2008)).

ix) Standardized unexpected earnings (SUE): the change in (split-adjusted) earnings relative to that in the same quarter during the previous fiscal year divided by month-end price (Ball and Brown (1968), Livnat and Mendenhall (2006)).

x) Idiosyncratic volatility (IVOL): the annualized volatility of the residuals from market model regressions (using daily data and the CRSP value-weighted index) for the issuer's equity within each month. See Ang et al. (2006) (using total equity volatility instead of idiosyncratic volatility has no material impact on any of the results in this article).

These equity market predictors are based on Stambaugh et al. (2012) and Chordia et al. (2014).[9] There are a number of predictors in the Stambaugh et al. list that are highly correlated with each other. For example, their real investment measure is very similar to asset growth. Their measure of net operating assets is also highly correlated with asset growth. Hence, we choose asset growth. Similarly, their three measures of profitability are highly correlated with each other, so we use our measure. Stambaugh et al. also use distress measures, which we capture via a measure of default risk, described later. The Chordia et al. list of anomalies adds size, book-to-market ratio, idiosyncratic volatility, and SUE, which completes our list.

Table 2 provides summary statistics on our equity return predictor variables for the bond–equity matched sample of all bonds and the subsamples of IG bonds and junk bonds. We observe that all of the equity market variables have greater standard deviations for junk bonds than they do for IG bonds. Also, the junk sample has high average idiosyncratic volatility, has high asset growth, and is unprofitable compared with the IG sample.

In our analysis, although our focus is on the equity-based bond return predictors, we also include the following bond-market-based measures as well: i) the 1-month lagged bond return (RBD1), to account for potential bond

[8] In unreported analysis, we also use gross profitability calculated as the ratio of gross profit to total assets (Novy-Marx (2013)). Our results are similar but weaker using this measure of profitability. For brevity, we do not report these results, but they are available from the authors.

[9] Recent work by Green, Hand, and Zhang (2013), Harvey, Liu, and Zhu (2015), and Bali, Engle, and Murray (2016) has compiled a list of over 300 different anomalies. We pick a few of the most well-known anomalies.

TABLE 2
Summary Statistics for Equity Return Predictors

Table 2 presents summary statistics for the equity return predictors used to predict the corresponding bond returns. Size (ln(MC)) is the natural logarithm of the market value of the equity of the firm. Value (ln(BM)) is the natural logarithm of the ratio of the book value of equity to the market value of equity. Momentum (REQ26) is the cumulative 5-month return on equity, starting from the second month prior to the current month. Lead–lag (REQ1) is the lagged monthly return on equity. Profitability (PROF) is the ratio of equity income (income before extraordinary items – dividend on preferred shares + deferred taxes) to book equity. Net stock issues (NETISS) is the change in the natural log of the split-adjusted shares outstanding. Accruals (ACCRU) is the ratio of accruals to assets, where accruals are defined as the change in (current assets – cash and short-term investments – current liabilities + short-term debt + taxes payable) less depreciation. Asset growth (ASTG) is the percentage change in total assets. Standardized unexpected earnings (SUE) is the change in (split-adjusted) earnings over the same quarter in the last fiscal year divided by price. Idiosyncratic volatility (IVOL) is the annualized volatility of the residuals from the market model regression for the issuer's equity over each month. Accounting variables are assumed to become available 6 months after the fiscal year-end. In Panel A, all statistics are computed first in the cross section, then in the time series. Panel B shows the cross-sectional correlations of all variables used in the cross-sectional regressions. RBD26 is the cumulative 5-month return on the bonds, starting from the second month prior to the current month; RBD1 is the lagged monthly return on bonds; DD is the distance to default; LEAMI is the Amihud illiquidity measure; ISZ is the bond issue size; MAT is the time to maturity in years; LEV is the book leverage, calculated as the ratio of book value of debt to the sum of book value of debt and book value of equity; and RATG is an ordinal value that assumes value of 1 for AAA-rated bonds, 2 for AA+ rated bonds, and so on. We compute the correlations each month and report the time-series average of these correlations. The sample period is 1973–2014.

Panel A. Descriptive Statistics

		All Bonds			IG			Junk		
Variable	N	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
ln(MC)	1,159,522	7.6	7.7	1.5	8.1	8.2	1.2	6.3	6.3	1.5
ln(BM)	1,109,230	−0.3	−0.3	0.7	−0.4	−0.3	0.6	−0.2	−0.1	0.9
REQ26	1,155,128	5.8	4.7	20.5	5.8	5.1	14.9	5.9	3.4	29.8
REQ1	1,159,522	1.1	0.9	9.1	1.2	1.0	6.8	1.1	0.5	13.0
PROF	1,102,671	−3.5	3.3	48.2	3.2	4.6	20.0	−20.5	−2.4	81.7
NETISS	1,127,472	3.6	1.2	9.9	2.8	1.0	8.4	4.9	1.4	12.6
ACCRU	872,184	−3.9	−3.7	4.8	−3.8	−3.6	3.9	−4.1	−3.8	6.7
ASTG	1,111,863	12.4	7.0	26.4	10.8	7.0	19.9	15.2	6.5	36.8
SUE	1,106,417	−0.3	0.1	10.4	−0.1	0.1	4.3	−0.8	0.2	18.1
IVOL	1,159,488	26.2	21.6	18.3	21.4	19.3	10.7	39.4	32.2	26.8

Panel B1. Cross-Sectional Correlations between Stock Variables

Variable	ln(BM)	REQ26	REQ1	PROF	NETISS	ACCRU	ASTG	SUE	IVOL
ln(MC)	−0.34	0.10	0.05	0.21	−0.05	−0.02	0.02	0.08	−0.41
ln(BM)		−0.22	−0.11	0.00	0.04	0.01	−0.11	−0.14	0.11
REQ26			0.01	−0.01	−0.05	−0.02	−0.05	0.14	−0.13
REQ1				0.00	−0.03	0.00	−0.03	0.03	0.04
PROF					−0.04	0.24	0.13	−0.10	−0.24
NETISS						0.08	0.43	0.01	0.04
ACCRU							0.22	−0.04	−0.05
ASTG								−0.05	0.04
SUE									−0.13

Panel B2. Cross-Sectional Correlations between Stock and Bond Variables

Variable	RBD26	RBD1	DD	LEAMI	ln(ISZ)	ln(MAT)	LEV	RATG
ln(MC)	−0.06	−0.02	0.49	−0.28	0.50	0.09	−0.29	−0.61
ln(BM)	−0.05	−0.01	−0.30	0.11	−0.07	0.01	−0.08	0.21
REQ26	0.20	0.04	0.08	−0.05	0.00	0.01	−0.02	−0.03
REQ1	0.02	0.11	0.03	−0.02	0.00	0.00	−0.01	−0.01
PROF	−0.07	−0.03	0.28	−0.11	0.00	0.03	−0.26	−0.27
NETISS	0.01	0.00	−0.06	−0.02	−0.03	0.00	0.15	0.14
ACCRU	−0.01	−0.01	0.04	0.00	−0.04	0.00	0.03	−0.02
ASTG	−0.03	−0.01	−0.01	−0.04	0.02	0.02	0.01	0.04
SUE	0.08	0.02	0.07	−0.06	0.00	0.01	−0.01	−0.06
IVOL	0.00	0.01	−0.55	0.28	−0.08	−0.07	0.17	0.47

Panel B3. Cross-Sectional Correlations between Bond Variables

Variable	RBD1	DD	LEAMI	ln(ISZ)	ln(MAT)	LEV	RATG
RBD26	−0.10	−0.06	0.01	−0.04	−0.02	0.05	0.11
RBD1		−0.03	0.00	−0.01	0.00	0.02	0.05
DD			−0.15	0.06	0.08	−0.42	−0.65
LEAMI				−0.11	−0.03	0.10	0.16
ln(ISZ)					0.19	−0.03	−0.16
ln(MAT)						−0.04	−0.11
LEV							0.43

market reversals; ii) the 2- to 6-month lagged bond return (RBD26) as a proxy for bond market momentum (Jostova et al. (2013));[10] iii) the DD (based on Merton (1974)) as an inverse proxy for default likelihood; iv) bond rating (RATG), which is the ordinal value that assumes a value of 1 for AAA-rated bonds, 2 for AA+ bonds, and so on; v) the natural log of the bond maturity (ln(MAT)) measured in years; and (vi) the natural log of the issue size in millions (ln(ISZ)). Firm leverage (LEV) is included because it can impact bond returns. Leverage is measured as the ratio of the book value of debt to the sum of the book value of debt and the book value of equity. In addition, we include a proxy for liquidity, the natural log of the Amihud (2002)-based liquidity measure from the equity market (LEAMI).[11]

Panel B1 of Table 2 presents the time-series averages of cross-sectional correlations between the equity variables, and Panel B2 presents correlations between both the equity- and bond-market-based return predictors and Panel B3 presents correlations between the bond variables. Among the more noteworthy results are as follows. Larger firms, more profitable firms, higher-rated firms, firms with a higher DD, and firms with higher earnings surprises have lower idiosyncratic volatility. Firms with higher asset growth also issue more shares and have higher accruals. Larger, more profitable firms have lower leverage, higher ratings, and a larger DD. Not surprisingly, higher-rated firms have a larger DD and lower leverage. Larger firms have a bigger bond issue size, which is in turn positively correlated with maturity.

A. The Testing Framework

The Merton (1974) model provides a simple relation between stock and bond returns. Suppose that excess returns on a representative stock and representative bond, $R_{e,t+1}$ and $R_{b,t+1}$, respectively, at time $t+1$, are driven by a factor whose realization at time $t+1$ is ε_{t+1}:

$$\begin{aligned} R_{e,t+1} &= \mu_{e,t} + \Delta_{e,t}\varepsilon_{t+1}, \\ R_{b,t+1} &= \mu_{b,t} + \Delta_{b,t}\varepsilon_{t+1}, \end{aligned} \tag{1}$$

where $\mu_{k,t}$ and $\Delta_{k,t}$, $k=\{e,b\}$ represent the expected return and the factor loading for equities and bonds at time t, respectively. Assume that the no-arbitrage condition holds, and there exists a stochastic discount factor, m, that prices both bonds and equities (which is the case in a setting with a representative agent). Then the

[10]Including longer lag versions of momentum, the 7- to 12-month equity and bond returns, results in a loss of sample size because of the restriction that a bond-month is dropped if any of the lagged return variables required for the momentum variable are missing. In unreported results, we find that including these longer lags leaves the main analysis substantively unaltered (one variable, ln(BM), becomes insignificant, but this is not the main focus of our paper, and its significance is not robust even in our presented analysis, as we will see).

[11]It is not feasible to construct a similar bond liquidity measure because we have daily data on only a small subsample of bonds. As we noted in footnote 3, the documented cross-correlation in stock and bond liquidity (Maslar (2013)) should ensure that stock liquidity at least partially proxies for bond liquidity.

Euler equations imply the following:

$$(2)\qquad \begin{aligned} \mu_{e,t} &= \frac{1}{\mathrm{E}_t m_{t+1}} \mathrm{cov}_t(m_{t+1}, R_{e,t+1}) &= \frac{\Delta_{e,t}}{\mathrm{E}_t m_{t+1}} \mathrm{cov}_t(m_{t+1}, \varepsilon_{t+1}), \\ \mu_{b,t} &= \frac{1}{\mathrm{E}_t m_{t+1}} \mathrm{cov}_t(m_{t+1}, R_{b,t+1}) &= \frac{\Delta_{b,t}}{\mathrm{E}_t m_{t+1}} \mathrm{cov}_t(m_{t+1}, \varepsilon_{t+1}). \end{aligned}$$

Combining these two Euler equations, we have:

$$(3)\qquad \mu_{b,t} = h_t \times \mu_{e,t},$$

where the hedge ratio, h_t, is defined by $h_t = \Delta_{b,t}/\Delta_{e,t}$. Equation (3) implies that in the rational, representative agent setting, equity characteristics that are associated with the equity premium affect the bond risk premium (holding h_t constant). Although Merton's structural model is an elegant framework for analyzing equity and bond returns simultaneously, we discuss two scenarios that lead us to consider why actual expected returns might deviate from this approach.

First, the anomaly literature suggests that a number of the equity characteristics listed previously cannot be reconciled in a rational framework, and the sign of the prediction in some cases is not consistent with risk-based arguments. For example, it is hard to argue that firms with lower accounting accruals should be riskier (i.e., load more heavily on the risk factor) and hence earn higher average returns (Fama and French (2008)). Based on this observation, suppose that the equity expected returns deviate from equation (2) for behavioral reasons (e.g., overconfidence or limited attention). In this scenario, bond returns might deviate from equation (2) in similar ways, provided investors have common biases across the two markets.

Next, suppose that bond market investors are largely rational, but equity market prices are, in part, driven by boundedly rational investors (the anomaly literature suggests that the converse is unlikely to hold). In this scenario, we would expect equation (2) to hold for bonds but not for equities (equation (3) would not hold either). Further, bond return predictors would be risk based, and the sign of the predictors would be consistent with risk pricing.

In either of the two scenarios, market segmentation and frictions might give rise to an additional source of predictability. With (partially) segmented markets, information might be transmitted from one market to another with a lag, creating a lead–lag relation, which would be an additional source of deviation from expected returns that would prevail in a perfect, frictionless, rational world. Further, rewards to liquidity provision might manifest themselves as return reversals (Jegadeesh (1990), Grossman and Miller (1988)).

Overall, to the extent that risk pricing shares commonalities between stocks and bonds, then bond returns would be related to stock returns via equation (3). However, market segmentation, investor biases, and frictions would cause bond returns to deviate from this equation. We thus consider two categories of possible reasons for bond return predictability from equity characteristics: i) the RR paradigm and ii) behavioral misreactions and frictions (including market segmentation). Table 3 provides the expected signs of the firm characteristics as bond return predictors, which we justify in Sections III.A.1–III.A.2. We then present regression coefficients and portfolio analyses in Sections III.B–III.C. Subsequently,

TABLE 3

Expected Signs of Equity Variables as Bond Return Predictors

Table 3 presents the predicted signs in a cross-sectional regression of corporate bond returns on lagged variables that capture equity return anomalies, under behavioral/friction-based arguments, and the rational risk–return paradigm. A + (−) means a positive (negative) coefficient, a ? implies no prediction, and a +/− implies either a positive or a negative coefficient, depending on the specific arguments. Equity return predictors are described in Table 2.

Variable	Risk–Return	Behavioral or Frictions
Size (ln(MC))	−	−
Value (ln(BM))	+	+
Momentum (REQ26)	?	+
Lead–lag (REQ1)	?	−/+
Profitability (PROF)	+/−	+
Net stock issues (NETISS)	?	+
Accruals (ACCRU)	?	−/+
Asset growth (ASTG)	−	−
Earnings surprise (SUE)	?	+
Idiosyncratic volatility (IVOL)	+/0	−

in Section IV, we use the insights of MacKinlay (1995) to consider whether the Sharpe-ratio magnitudes corresponding to bond return predictors (both gross and net of transaction costs) are consistent with risk-based rationales.

1. The Risk–Reward Paradigm

The RR arguments link characteristic-based predictability to risk compensation. We now discuss the likely direction of prediction for each of the variables with and without our controls for risk, where the latter include the Fama–French (2015) factors based on the market, size, book-to-market ratio, profitability, and investment and 2 bond market factors based on the credit spread and term-structure slope (see Section III.C.3 for more detail). Note that we also control for the DD, firm leverage, and bond ratings. Nonetheless, risk-related variables could still be priced if our factors do not completely capture risk in the corporate bond market.

The signs appear unambiguous in only a few cases under the RR paradigm. Thus, if size and book-to-market ratio capture distress risk (Fama and French (1993)), we would expect firm size to have a negative sign and book-to-market ratio to have a positive sign because firms with higher distress risk (small firms and firms with a high book-to-market ratio) should require higher bond returns. We would expect such predictability to be mitigated after we control the Fama–French (2015) risk factors that account for the market, as well as the effects of size and book-to-market ratio.

With regard to profitability, Hou et al. (2015) argue that all else being equal, more profitable firms should have higher discount rates because with high profitability, high discount rates are required for firms to be in a state of equilibrium where they do not want to invest more (see also Fama and French (2015)). Novy-Marx (2013) and Fama and French do find that more profitable firms earn higher equity returns. Fama and French and Hou et al. argue that profitability represents a risk factor on which stocks load positively. If bond loadings on the profitability factor also are positive, then we would expect bond returns to also be positively associated with profitability, but adjusting returns for risk factors should make the relation disappear.

There is, however, another argument that profitable firms might be less prone to default, and the bonds of such firms therefore could be safer. Safer bonds would tend to have lower loadings on common factors and also have less total risk of default. We would expect profitability to be associated with *lower* required returns without risk controls. However, if default risk is largely diversifiable, this profitability–return relation should weaken or disappear after properly controlling for risk. Overall, the sign on profitability under the RR paradigm can be positive or negative before systematic risk controls, but we expect a weakened relation (or no relation) after the controls.

Turning now to IVOL, if investors do not hold diversified portfolios, higher IVOL should imply (albeit imperfectly) higher uncertainty about assets' (and thus bonds') cash flows and thus imply higher expected bond returns so that, as per risk-return-based arguments, we predict positive coefficients for IVOL. Of course, if investors are well diversified, then the coefficient on IVOL will be close to 0. Finally, Hou et al. (2015) argue that firms with higher investment (and consequently higher asset growth) must be those with lower equity and bond expected returns. By this argument, the coefficient on ASTG should be negative but, again, weaken after controlling for the investment-based factor, which is part of the Fama–French (2015) set of factors.

The role of the other variables under the RR paradigm appears hard to predict, so we leave these signs unspecified.

2. Behavioral and Frictions

We now turn to the hypotheses based on behavioral arguments and market frictions. For developing these hypotheses, we assume that investors' behavioral biases are similar across equity and debt markets. For example, the accruals effect represents an overly high focus on earnings relative to cash flow, and this argument implies overvaluation in the presence of high accruals and negative future returns as the overvaluation is corrected in both bonds and equities. An underreaction to profits should lead to undervaluation and, thus, a positive relation between profitability and future expected returns for both bonds and equities. Similarly, a preference for the bonds of lottery-like volatile companies (Kumar (2009)) would result in a negative coefficient on IVOL. Barberis et al. (1998) and Daniel et al. (1998) have argued that behavioral biases such as representativeness, overconfidence, and self-attribution can lead to the momentum effect in stock returns. If the impact of past stock returns spills over from equities to bonds, as suggested by Gebhardt et al. (2005b), then we would expect a positive coefficient on REQ26. Further, if the overconfidence-based rationales for overreaction (Daniel et al.) also apply in the bond market, we expect a negative (positive) coefficient on size (book-to-market ratio) in the bond market, just as in equities.

We expect NETISS to have a positive coefficient in the bond market, in contrast to its negative sign in the equity market. This is because the market-timing hypothesis (Daniel and Titman (2006)) posits a preference for equity over debt when equities are overvalued and/or the debt is *undervalued*, which implies a positive relation between NETISS and future bond returns.

We now turn to REQ1. Under either the overreaction/correction hypothesis (Cooper (1999)) or the illiquidity hypothesis (Grossman and Miller (1988)), we would predict the past month's bond return to be negatively related to this month's bond return. If bond returns and equity returns contain a common overreaction component, and bond returns are imperfect proxies for this component (e.g., owing to errors induced by stale prices), then we might expect REQ1 to predict bond returns with a negative sign, even after controlling for the lagged bond return. However, although corporate bond markets consist of more sophisticated investors than stock markets (Edwards et al. (2007)), stocks are more liquid than corporate bonds (Maslar (2013)). This greater liquidity could attract a large mass of diversely informed traders (Admati and Pfleiderer (1988)) to equity markets, and the aggregate information of these traders might be pertinent for bond prices but be reflected in stock prices first. In this scenario, bond markets could react to stock markets with a lag, and the coefficient of REQ1 might be positive. Hence the sign of the coefficient of REQ1 can be positive or negative, depending on the relative validity of the overreaction and the delay-based arguments.

B. Fama–MacBeth Regressions

We first examine the impact of the firm-level characteristics on stock returns and then on bond returns. We winsorize all the right-hand-side variables at the 0.5th and 99.5th percentiles each month. We also scale each anomaly variable by its cross-sectional standard deviation each month so that the coefficient magnitudes are comparable to each other. The dependent variable is in basis points (bps) per month.

Table 4 presents the Fama–MacBeth (1973) coefficient estimates from the following cross-sectional regression each month:

$$R_{it}^{e} = \nu_{0t} + \nu_{1t}' \mathrm{ZEQ}_{it-1} + \upsilon_{it}, \tag{4}$$

where R_{it}^{e} is the excess stock return, and ZEQ_{it-1} represents lagged equity return predictors (the momentum returns are lagged by an additional month). The predictors are described in Table 2. t-statistics with Newey–West (1987) correction are given in parentheses.[12] We present results for the full sample and the matched sample. The full sample includes all firms with available data, and with a price per share greater than $1 as of the end of the prior month. The matched sample includes only those firms for which we have corresponding bond returns.

We note that our corporate bond sample, in market capitalization, is much closer to the full sample of equities, as opposed to the matched sample in Table 4. Thus, for example, the median firm in the full sample has an equity market capitalization of $134 million, whereas the corresponding number for the matched sample is as high as $2 billion. The median bond issue, conversely, has a market value of $102 million, putting it much closer to the median equity market capitalization for the full sample. Because the matched equity sample consists of larger firms, which are presumably more efficiently priced (Fama and French (2008)), we would expect the anomalies to manifest themselves less strongly in this sample than in the full sample. Indeed, in the full sample, we find that all of the firm characteristics impact the cross section of stock returns, and the signs

[12]Based on Newey and West (1994), the lag length L is chosen as the integer part of $4(T/100)^{2/9}$, where T is the number of observations.

TABLE 4

Monthly Cross-Sectional Regressions for Stock Returns

Table 4 presents the results from running the following cross-sectional regression each month:

$$R^e_{it} \quad = \quad \nu_{0t} + \nu'_{1t}\mathrm{ZEQ}_{it-1} + \upsilon_{it},$$

where R^e_{it} is the excess stock return, and ZEQ_{it-1} represents lagged equity return predictors, which are described in Table 2. *t*-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. Column 1 presents results for all stocks with a price greater than $1, whereas column 2 presents results for only those stocks for which we have corresponding bond returns. The sample period is 1973–2014, excluding the months between May 1998 and Mar. 2001, for which we do not have enough firm observations to run the regressions in the matched sample.

Variable	Full Sample 1	Matched Sample 2
ln(MC)	−21.00** (−3.34)	−13.28** (−2.52)
ln(BM)	17.37** (2.24)	8.02 (1.44)
REQ26	16.05** (2.91)	1.95 (0.27)
REQ1	−59.75** (−8.86)	−22.78** (−3.91)
PROF	10.13** (2.52)	3.12 (0.55)
NETISS	−14.09** (−4.91)	−13.11** (−3.36)
ACCRU	−12.17** (−5.32)	−2.46 (−0.67)
ASTG	−16.74** (−5.20)	−8.60** (−2.28)
SUE	30.44** (9.71)	11.56** (2.28)
IVOL	−23.90** (−3.64)	−6.85 (−1.03)

are consistent with those in the earlier literature. But, in the sample matched with corporate bond data, we find that value, momentum, profitability, accruals, and idiosyncratic volatility are not significant. However, given that the median market capitalization of corporate bonds accords more with that of equities in the full sample, we include all characteristics in our Fama–MacBeth (1973) regressions for bonds, including those that are not significant for the matched sample.

We now ask which of our equity and bond characteristics have marginal power to predict bond returns. Our regression specification is

$$R_{it} \quad = \quad \gamma_{0t} + \gamma'_{1t} Z_{it-1} + \epsilon_{it}, \tag{5}$$

where R_{it} is the excess bond return, and Z_{it-1} is the full set of lagged equity- and bond-based predictors. Table 5 presents the results. The first regression shows that ln(MC) and ln(BM) are negatively priced when both are included in the regression. In univariate regressions (not shown), ln(BM) is positively priced. The coefficient on ln(BM) becomes even more negative and significant when the bond variables (especially the DD and bond ratings) are included in the cross-sectional regressions. The third and fourth regressions demonstrate that the coefficients on the lagged 1-month equity return and the longer-term equity returns, REQ26, become more strongly significant when the bond market variables are included.

TABLE 5

Monthly Cross-Sectional Regressions for Bond Returns

Table 5 presents the results from running the following cross-sectional regression each month:

$$R_{it} \quad = \quad \gamma_{0t} + \gamma_{1t}' Z_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, and Z_{it-1} represents lagged return predictors, which are described in Table 2. t-statistics with Newey–West (1987) correction (using 5 lags) for the average coefficients are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014.

Variable	1	2	3	4	5	6	7	8	9
ln(MC)	−6.99**	0.23							−1.17
	(−4.32)	(0.12)							(−0.54)
ln(BM)	−1.45	−4.04**							−3.04*
	(−1.35)	(−3.14)							(−1.95)
REQ26			4.49**	10.30**					9.67**
			(4.04)	(8.92)					(8.72)
REQ1			10.69**	14.76**					12.68**
			(8.70)	(9.21)					(7.21)
PROF					−6.43**	−4.66**			−5.06**
					(−4.95)	(−5.36)			(−3.73)
NETISS					−0.35	−1.09			−0.27
					(−0.39)	(−1.37)			(−0.21)
ACCRU							−0.24	0.07	1.34
							(−0.36)	(0.08)	(1.14)
ASTG							−2.71**	−2.65**	−2.00**
							(−3.27)	(−3.47)	(−2.22)
SUE							0.63	1.85	−0.25
							(0.53)	(1.68)	(−0.18)
IVOL							5.59**	0.61	−0.75
							(2.84)	(0.34)	(−0.46)
RBD26		−12.47**		−15.27**		−12.41**		−12.18**	−15.71**
		(−5.25)		(−6.36)		(−5.31)		(−5.50)	(−6.42)
RBD1		−42.60**		−45.43**		−41.82**		−43.74**	−47.54**
		(−12.26)		(−12.70)		(−12.57)		(−12.88)	(−13.06)
DD		−2.12		−3.23**		0.86		1.40	−2.39
		(−1.39)		(−2.23)		(0.60)		(1.10)	(−1.30)
LEAMI		3.28**		4.21**		2.59**		2.20	2.95**
		(3.07)		(3.75)		(2.45)		(1.58)	(2.01)
ln(ISZ)		−1.06		−0.61		−0.85		−1.31	−1.29
		(−0.98)		(−0.55)		(−0.81)		(−1.06)	(−1.01)
ln(MAT)		−5.75		−5.89		−5.22		−4.31	−4.74
		(−1.63)		(−1.63)		(−1.50)		(−1.22)	(−1.31)
LEV		−0.41		−0.45		0.20		1.33	−0.96
		(−0.36)		(−0.42)		(0.20)		(1.05)	(−0.72)
RATG		7.99**		7.73**		8.02**		9.11**	7.13**
		(3.50)		(3.61)		(3.97)		(3.98)	(2.86)

The next 4 regressions demonstrate that the coefficients on profitability, PROF, and asset growth, ASTG, are robust to the inclusion of the bond market variables, whereas the coefficient on idiosyncratic volatility, IVOL, is not.[13] Column 9 presents results for all of the variables and documents the significant results for ln(BM), the lagged equity returns, PROF, and ASTG.

[13]Panel B of Table 2 shows that the unconditional correlations of RATG with PROF and ASTG are −0.27 and 0.04, respectively, but the correlation between RATG and IVOL is 0.47, and is thus much higher in absolute terms than the other two. This accords with the material impact of ratings on the IVOL coefficient.

The final regression of Table 5 documents that a 1-standard-deviation change in ln(BM), REQ1, REQ26, PROF, and ASTG impact bond market returns by 3.04, 12.68, 9.67, 5.06, and 2.00 bps per month, respectively. The economic impact of ASTG is the smallest, whereas that of REQ1 is the largest. In Section IV, we examine the impact of transaction costs on the profitability of the corresponding investment strategies.

In terms of the bond market controls, we find that the coefficient on lagged 1-month bond return is negative and strongly significant, which is consistent with illiquidity in the corporate bond market causing an inventory-based reversal (Grossman and Miller (1988)). The negative and significant coefficient on the past 2- to 6-month bond returns is noteworthy. It is possible that investors overly react to improvements or deterioration in credit risk, and the negative coefficient on RBD26 is the result of the subsequent correction. The coefficient on DD is negative and significant in the absence of bond ratings. The significantly positive coefficient on ratings is consistent with its interpretation as a default risk proxy, suggesting that riskier bonds with higher numerical rating scores earn higher returns. This is in contrast to equities, where returns on low-rated stocks (Compustat and RatingsXpress provide overall firm ratings) earn lower returns than high-rated stocks (see Avramov, Chordia, Jostova, and Philipov (2013)). Finally, the coefficient on the liquidity variable, LEAMI, is 2.95, with a *t*-statistic of 2.01. Thus, returns are higher for bonds with greater equity illiquidity, consistent with the notion that equity and bond illiquidity are cross-correlated (Maslar (2013)) so that the coefficient on equity illiquidity partially proxies for a liquidity premium in bonds.

Note that the signs of the coefficients on PROF and ASTG are consistent with RR arguments. This is because more profitable firms and firms that invest a lot (i.e., firms with more assets and thus more collateral) are likely to be less risky from the perspective of bondholders and thus earn lower bond returns.[14]

Comparing the coefficient magnitudes for stocks and corporate bonds in Tables 4 and 5, respectively, we find that given the limited upside potential because of the lower volatility for corporate bonds compared with equities, the economic impact of the anomalies is also smaller in the former market. Thus, focusing on the full sample in Table 4 and column 9 in Table 5, 1-standard-deviation changes in PROF and ASTG impact bond (stock) returns by 5.06 (10.13) and 2.00 (16.74) bps per month, respectively. The standardized impact of REQ26 is also smaller (16.05 for the full equity sample vs. 9.67 in column 9 of Table 5). Moreover, the insignificance of accruals, idiosyncratic volatility, and earnings surprises does not accord with the evidence for equity returns and is not consistent with the behavioral arguments of Table 3. At the same time, the coefficient estimate on ln(BM) in column 9 of Table 5 (-3.04, with *t*-statistic $= -1.95$), although only marginally significant, does not accord with the RR paradigm. Thus, if, as suggested by Fama and French (1993), the book-to-market ratio proxies for distress risk, then the coefficient on ln(BM) should be positive. We will soon see, however, that the marginal significance of ln(BM) is not robust to risk controls.

[14]Later we will present Fama–MacBeth (1973) regression results using risk-adjusted returns.

C. Robustness Checks

1. Single-Bond Return per Firm

One concern is that firms with large numbers of distinct bond issues can have a material impact on the cross-sectional relations that we are testing. For instance, firms like General Motors can have several different bonds with varying coupons and maturities. If these firms experience a material event such as restructuring, their financial distress could have a large impact on the cross-sectional relation between bond returns and such variables as book-to-market ratio and ratings because we treat each individual bond as a separate cross-sectional observation.

To address this issue, we now report the results of cross-sectional regressions that use 1 bond per firm. For firms that have more than 1 bond issue outstanding, we use four different methods to choose one of the issues: i) we randomly choose a bond issue, ii) we choose an issue with the shortest remaining maturity as long as it is more than 1 year, iii) we choose the most recent bond issue, and iv) we use the equal-weighted average of the bond returns across each firm. The second and third procedures are motivated by Bao et al. (2011), who show that the most recent issue and the issue with the shortest maturity are, in fact, the most liquid ones. Table 6 presents the results. In general, the results are the same as those in Table 5.

2. Risk-Adjusted Returns

To control for risk, we now follow the methodology of Brennan, Chordia, and Subrahmanyam (1998) and use risk-adjusted returns instead of excess returns as the dependent variable in the Fama–MacBeth (1973) regressions. The results are presented in Table 7. In order to compute risk-adjusted returns, we use full-sample betas and only bonds with at least 24 months of data. This causes a decrease in the sample size. The total number of observations is reported in the last row. The first column uses no adjustment (and is, therefore, identical to regression 9 in Table 5). The second column uses the market, stock size, and stock value factors from Fama and French (1993) (FF3) plus 2 bond factors (TRM and DEF).[15] The third column uses the market, stock size, stock value, firm investment, and firm profitability factors from Fama and French (2015) (FF5); 2 bond factors (TRM and DEF); and the Pástor and Stambaugh (2003) liquidity factor, PSL. The last 2 columns add the bond liquidity factors of Lin et al. (2011) to the mix.[16] The sharp decline in sample size for the last 2 columns occurs because the sample period for the bond liquidity factors is only 2002–2009. In the regressions that adjust returns for bond liquidity factors, we also include Bao et al. (2011) bond liquidity, BPW, because liquidity betas are known to vary with the level of liquidity (at least for equities). BPW is calculated as the autocovariance of excess bond returns:

$$\mathrm{BPW} \quad = \quad (-\mathrm{cov}_t(\Delta p_{itd+1}, \Delta p_{itd}))^{0.5},$$

[15] TRM is the difference in returns between long-term Treasury bonds and Treasury bills, and DEF is the difference in returns between the corporate bond market portfolio and long-term Treasury bonds (data on these variables are obtained from Ibbotson).

[16] We thank Junbo Wang for providing the bond liquidity factors.

TABLE 6

Monthly Cross-Sectional Regressions for Bond Returns: Single Bond Return per Firm

Table 6 presents the results from running the following cross-sectional regression each month:

$$R_{it} \quad = \quad \gamma_{0t} + \gamma'_{1t} Z_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, and Z_{it-1} represents lagged return predictors, which are described in Table 2. t-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. We run the regression using only 1 bond return per firm. This bond return is for a bond chosen at random or chosen to have the shortest maturity or the lowest age, or the bond return is an equal-weighted average of all bond returns for a given firm in a given month. The sample period is 1973–2014, excluding the months between May 1998 and Mar. 2001, for which we do not have enough firm observations to run the regressions.

Variable	Randomly Chosen	Shortest Maturity	Lowest Age	Average within Firm
ln(MC)	−2.04	−1.83	−2.80	−1.75
	(−1.46)	(−1.37)	(−1.41)	(−0.99)
ln(BM)	−1.98	−2.22**	−3.41**	−2.25**
	(−1.61)	(−2.08)	(−2.80)	(−2.30)
REQ26	5.59**	5.50**	8.84**	6.97**
	(7.36)	(6.76)	(8.56)	(8.68)
REQ1	11.05**	11.28**	14.57**	12.51**
	(9.84)	(10.03)	(10.21)	(10.65)
PROF	−2.86**	−2.58**	−3.06**	−2.88**
	(−2.94)	(−2.85)	(−2.94)	(−3.24)
NETISS	0.63	1.10	0.71	1.10
	(0.82)	(1.80)	(0.84)	(1.72)
ACCRU	0.17	0.82	0.28	0.55
	(0.26)	(1.38)	(0.42)	(0.97)
ASTG	−2.35**	−2.40**	−2.56**	−2.84**
	(−2.50)	(−2.82)	(−2.68)	(−3.85)
SUE	0.65	0.75	0.74	0.93
	(0.75)	(0.83)	(0.68)	(1.09)
IVOL	−0.83	−0.17	−1.00	−0.92
	(−0.55)	(−0.14)	(−0.67)	(−0.71)
RBD26	−5.57**	−10.17**	−11.94**	−9.55**
	(−4.26)	(−5.42)	(−6.73)	(−5.11)
RBD1	−21.66**	−35.78**	−42.88**	−30.07**
	(−12.57)	(−13.24)	(−15.42)	(−12.62)
DD	−0.49	−1.56	−3.30**	−1.55
	(−0.44)	(−1.62)	(−2.94)	(−1.69)
LEAMI	2.37**	2.51**	2.80**	2.35**
	(1.98)	(2.06)	(2.08)	(1.97)
ln(ISZ)	−0.33	−0.44	−0.18	−0.35
	(−0.30)	(−0.48)	(−0.14)	(−0.29)
ln(MAT)	−1.93	−1.56	−3.04	−3.14
	(−0.62)	(−0.57)	(−0.74)	(−1.21)
LEV	−0.28	0.48	−0.36	0.36
	(−0.27)	(0.49)	(−0.35)	(0.39)
RATG	8.18**	7.90**	7.73**	7.33**
	(3.65)	(4.27)	(3.45)	(3.14)

where Δp_{itd} is the ln price change on bond i on day d of month t, and BPW is the Roll (1984) measure of the effective bid–ask spread. We calculate BPW using daily data starting in 2002.

The results in the first 3 columns of Table 7 are essentially the same (the exceptions are the coefficients on RATG and ln(BM) when risk-adjusting with FF5 + PSL), suggesting that risk adjustment by FF3 + DEF + TRM and by FF5 + DEF + TRM + PSL does not significantly impact the characteristic premiums,

TABLE 7

Monthly Cross-Sectional Regressions for Bond Returns: BCS Analysis

Table 7 presents the results from running the following cross-sectional regression each month:

$$R_{it} - \hat{\beta}_i F_t = \gamma_{0t} + \gamma'_{1t} Z_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, and Z_{it-1} represents lagged return predictors, which are described in Table 2. Returns on the left-hand side are adjusted following Brennan et al.'s (1998) methodology. We use full-sample betas and only bonds with at least 24 months of data. The total number of observations (N) is reported in the last row. Column 1 uses no adjustment (and is therefore identical to regression 9 in Table 5). Column 2 uses the market, stock size, and stock value factors from Fama and French (1993) (FF3), plus 2 bond factors (TRM and DEF). TRM is the return on long-term Treasury bonds in excess of T-bills, and DEF is the return on the corporate bond market portfolio in excess of the long-term Treasury bond. Column 3 uses the market factor, stock size and value factors, and firm investment profitability factors from Fama and French (2015) (FF5); 2 bond factors (TRM and DEF); and the Pástor and Stambaugh (2003) liquidity factor, PSL. Columns 4 and 5 add the bond liquidity factors of Lin et al. (2011) to the mix. In the regressions that adjust returns for bond liquidity factors, we also include Bao et al. (2011) bond liquidity, BPW, as an additional control variable. *t*-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014 except in the last 2 columns, where it is 2002–2009.

Variable	No Adjustment 1	FF3 + DEF + TRM 2	FF5 + PSL 3	FF3 + DEF + TRM + BONDL 4	FF5 + PS + BONDL 5
ln(MC)	−1.17	−1.36	−0.10	10.43	18.39
	(−0.54)	(−0.71)	(−0.04)	(1.21)	(1.11)
ln(BM)	−3.04*	−3.69**	−1.85	−32.85	−42.51
	(−1.95)	(−2.71)	(−1.39)	(−1.09)	(−1.14)
REQ26	9.67**	9.75**	9.22**	11.53	10.92
	(8.72)	(8.67)	(9.43)	(0.97)	(0.85)
REQ1	12.68**	10.79**	10.22**	26.19**	23.72**
	(7.21)	(7.19)	(6.83)	(4.88)	(6.45)
PROF	−5.06**	−3.71**	−4.46**	−14.73**	−8.30
	(−3.73)	(−3.29)	(−3.92)	(−1.97)	(−1.17)
NETISS	−0.27	0.10	0.63	13.69	14.34*
	(−0.21)	(0.08)	(0.57)	(1.52)	(1.66)
ACCRU	1.34	1.47	1.79*	4.22	4.98
	(1.14)	(1.61)	(1.86)	(1.44)	(1.49)
ASTG	−2.00**	−1.81**	−2.90**	−16.17	−14.30
	(−2.22)	(−2.01)	(−2.74)	(−1.46)	(−1.42)
SUE	−0.25	0.34	1.14	−18.69	−19.84
	(−0.18)	(0.39)	(0.91)	(−1.17)	(−1.15)
IVOL	−0.75	0.28	0.74	8.98	6.05
	(−0.46)	(0.17)	(0.39)	(0.65)	(0.43)
RBD26	−15.71**	−15.73**	−14.28**	−27.01**	−24.32**
	(−6.42)	(−7.55)	(−5.94)	(−3.43)	(−3.87)
RBD1	−47.54**	−45.30**	−43.80**	−70.67**	−68.10**
	(−13.06)	(−13.59)	(−13.56)	(−10.09)	(−9.44)
DD	−2.39	−3.51*	−2.09*	−4.79	−9.40
	(−1.30)	(−1.82)	(−1.64)	(−0.71)	(−1.15)
LEAMI	2.95**	4.94**	4.17**	−23.21	−15.53
	(2.01)	(3.73)	(2.97)	(−1.31)	(−1.20)
ln(ISZ)	−1.29	−0.44	−0.80	4.66	6.73
	(−1.01)	(−0.43)	(−0.74)	(0.69)	(0.94)
ln(MAT)	−4.74	−3.84	−2.04	−5.35	−9.80
	(−1.31)	(−1.25)	(−0.65)	(−0.81)	(−1.57)
LEV	−0.96	−3.26	−1.38	5.96	2.34
	(−0.72)	(−1.88)	(−0.96)	(1.24)	(0.44)
RATG	7.13**	5.31**	2.73	31.02	36.20
	(2.86)	(2.73)	(1.06)	(1.26)	(1.00)
ln(BPW)				−1.73	0.20
				(−0.43)	(0.04)
N	529,123	517,153	517,153	20,245	20,245

although the coefficient on ln(BM) becomes insignificant in the FF5 + PSL risk adjustment. When we add the bond liquidity factor to the pricing models and include the level of bond liquidity, the sample size is dramatically different, and it becomes difficult to compare with the earlier results. However, past bond returns and the past 1-month equity returns still have a significant characteristic premium. Profitability also has a significant premium when risk adjusting with FF3 + DEF + TRM and the bond liquidity factor but not when risk-adjusting with FF5 + PSL and the bond liquidity factor.

3. Subsample Analysis

In this section, we examine the impact of the different equity and bond variables on the bond excess returns for different subsamples. The motivation is to discriminate between the different explanations for the Fama–MacBeth (1973) coefficient estimates (i.e., the characteristic premiums). Thus, if investor behavioral biases drive returns, then the coefficient estimates should be stronger when sentiment is high (Stambaugh et al. (2012)). Conversely, if cross-sectional predictability in bonds arises from risk premia that are related to business-cycle risk (Fama and French (1989)), then the characteristic premiums should vary with the state of the business cycle and with variables that vary with business cycles.

We initially break down the full sample of 1973–2014 into two categories that are, in turn, based on sentiment, the National Bureau of Economic Research (NBER) recession dummy, and the market return (a proxy for the state of the economy). The sentiment variable is the standard Baker and Wurgler (2006) sentiment index. A high-sentiment month is one in which the value of the sentiment index in the previous month is above the median value for the sample period, and the low-sentiment months are all other months. The market return proxy is the return (including dividends) on the Standard & Poor's (S&P) 500. We also present results after excluding the years 2007–2009 as they pertain to the financial crisis. Table 8 presents the results.

First consider subsamples delineated by sentiment and market returns. The characteristic premium on value is negative and significant in months following high sentiment and in months with negative market returns. The value premium is significant during expansions as well, albeit significant only at the 10% level. Bonds of firms with high asset growth also seem to earn negative premiums during recessions and surprisingly when market returns are positive. Profitability does not seem to impact bond returns differently across high- and low-sentiment states or high and low market returns, although the coefficient on profitability is more negative during expansions compared with recessions. The coefficient estimates on past returns are all positive and significant across all subperiods. In terms of bond characteristics, stark differences across subsamples are evident in the case of ratings. Poorly rated bonds, that is, bonds with high credit risk, earn lower returns in down markets but higher returns during up markets and during expansions. Also note that bonds with longer maturities earn lower returns following high sentiment and during down markets.

The previous discussion indicates that there are no clearly interpretable patterns in how the characteristic premiums vary across different states. In unreported states, we statistically compare the coefficients across the subsamples based on

TABLE 8

Monthly Cross-Sectional Regressions for Bond Returns: Subsample Analysis

Table 8 presents the results from running the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma'_{1t} Z_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, and Z_{it-1} represents lagged return predictors, which are described in Table 2. t-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The full sample of 1973–2014 is broken into two categories based on sentiment, economic state, market return, or financial crisis. The sentiment variable is based on the Baker and Wurgler (2006) sentiment index. A high-sentiment month is one in which the value of the sentiment index in the previous month is above the median value for the sample period, and the low-sentiment months are those with below-median values. Economic state is based on the National Bureau of Economic Research (NBER) recession dummy. Market return states are based on return (including dividends) on the Standard & Poor's 500 (S&P 500). Finally, we denote years 2007–2009 as financial crisis years.

	Sentiment		Economic State		Market Return		
Variable	High	Low	Expansion	Recessions	Up	Down	Ex-Financial Crisis
ln(MC)	−0.87	−1.49	−1.95	3.28	2.33	−6.84	−1.50
	(−0.31)	(−0.50)	(−0.87)	(0.50)	(0.81)	(−1.35)	(−0.70)
ln(BM)	−4.72**	−1.24	−3.32*	−1.45	−1.35	−5.79**	−2.90*
	(−2.08)	(−0.76)	(−1.90)	(−0.49)	(−0.62)	(−2.39)	(−1.77)
REQ26	11.28**	7.95**	9.21**	12.29**	7.76**	12.77**	9.22**
	(6.84)	(5.64)	(7.43)	(4.90)	(6.27)	(6.48)	(8.12)
REQ1	14.08**	11.19**	11.43**	19.74**	11.09**	15.27**	11.61**
	(5.87)	(4.23)	(6.48)	(3.74)	(6.07)	(4.65)	(6.59)
PROF	−4.22**	−5.96**	−5.57**	−2.18	−5.77**	−3.91**	−5.06**
	(−2.78)	(−2.78)	(−3.78)	(−0.82)	(−3.23)	(−2.23)	(−3.58)
NETISS	1.11	−1.75	−0.61	1.65	−0.10	−0.54	−0.47
	(0.75)	(−0.67)	(−0.41)	(0.82)	(−0.05)	(−0.30)	(−0.34)
ACCRU	0.76	1.97	1.63	−0.27	1.91	0.43	1.61
	(0.67)	(1.11)	(1.23)	(−0.14)	(0.91)	(0.31)	(1.27)
ASTG	−3.28**	−0.64	−1.63*	−4.12**	−2.51*	−1.17	−1.85*
	(−2.84)	(−0.35)	(−1.65)	(−2.08)	(−1.67)	(−0.75)	(−1.95)
SUE	0.24	−0.77	−0.34	0.31	−0.27	−0.21	−0.06
	(0.11)	(−0.50)	(−0.24)	(0.09)	(−0.15)	(−0.11)	(−0.04)
IVOL	−2.38	1.00	0.09	−5.48	−0.32	−1.44	−0.30
	(−1.11)	(0.41)	(0.05)	(−1.51)	(−0.18)	(−0.50)	(−0.18)
RBD26	−17.74**	−13.54**	−13.40**	−28.79**	−16.63**	−14.23**	−14.17**
	(−6.43)	(−3.40)	(−5.69)	(−3.30)	(−5.82)	(−3.88)	(−6.19)
RBD1	−46.46**	−48.69**	−43.74**	−69.08**	−45.53**	−50.80**	−44.61**
	(−8.55)	(−10.62)	(−11.21)	(−9.18)	(−9.62)	(−9.40)	(−12.26)
DD	−4.83	0.22	−2.86	0.28	−3.19	−1.09	−1.89
	(−1.59)	(0.10)	(−1.34)	(0.12)	(−1.61)	(−0.39)	(−0.96)
LEAMI	2.78*	3.13	3.63**	−0.89	3.46	2.13	2.98*
	(1.67)	(1.46)	(2.18)	(−0.33)	(1.50)	(1.18)	(1.88)
ln(ISZ)	−2.25	−0.26	−1.58	0.34	1.56	−5.91**	−1.45
	(−1.21)	(−0.17)	(−1.19)	(0.09)	(0.98)	(−2.41)	(−1.12)
ln(MAT)	−11.76**	2.76	−3.20	−13.48	6.80	−23.47**	−3.10
	(−2.61)	(0.51)	(−1.00)	(−0.89)	(1.61)	(−4.25)	(−1.05)
LEV	−1.72	−0.15	−1.04	−0.50	1.44	−4.86**	−0.59
	(−0.83)	(−0.09)	(−0.72)	(−0.15)	(0.81)	(−2.49)	(−0.42)
RATG	7.70**	6.53*	9.64**	−7.06	18.55**	−11.39**	8.10**
	(2.53)	(1.75)	(4.09)	(−0.92)	(6.59)	(−2.09)	(3.40)

sentiment, economic state, and market returns. We find that there are no statistical differences in the coefficients on equity return predictors across high- and low-sentiment months, or across expansions and recessions. Thus, unlike Stambaugh et al. (2012) in the case of equities, our results for corporate bonds do *not* support the notion that cross-sectional predictability arises due to investor sentiment, which is reflected more in markets during optimistic periods (where acting on sentiment involves buying) than during pessimistic periods (where short-selling constraints preclude trading on sentiment). The only stock variable that shows a statistical difference across any of the subsamples is REQ26 across up and down markets, with higher significance in down markets. Among the bond characteristics, apart from the differences noted previously, the coefficients on RBD1 in expansions versus recessions and on ln(ISZ) and LEV in up and down markets are statistically significantly different. Again, an interpretation of these differences is elusive and perhaps better addressed in future research on the topic.

A noteworthy observation is that the results in Table 5 are, in general, robust to excluding the financial crisis period. The same variables (book-to-market ratio, bond and stock past returns, profitability, asset growth, ratings, and the Amihud illiquidity measure) continue to have significant coefficients.

In Table 9, we run a multivariate time-series regression to relate the characteristic premiums to three variables known to vary with the business cycle; these variables are the PAYOUT, the TRM_SPR, and the DEF_SPR (Ferson and Harvey (1991), Floyd, Li, and Skinner (2015)). PAYOUT is the ratio of the sum of the last-12-month dividends to the price of the S&P 500 index, TRM_SPR is the difference in the yield on long-term government bonds and 3-month Treasury bill rate, and DEF_SPR is the difference in the yield on BAA- and AAA-rated bonds. The results suggest that the characteristic premiums on past equity returns vary with the payout ratio, and those on profitability (weakly) vary with the payout ratio and the term spread, whereas those on ln(BM) and asset growth do not vary with any of these 3 variables. The effect of past bond returns and leverage also varies with the default spread (but the baseline coefficient for leverage is not significant in Table 5). The results for past equity and bond returns are not easily explained and are left for future work. Note, however, that because the baseline coefficient of PROF is negative, our results indicate that the bond market premium for less profitable firms attenuates when economic conditions improve (i.e., when the payout ratio and the term spread increase), which is consistent with intuition.

4. Portfolio Sorts and Factor Alphas

Because the Fama–MacBeth (1973) regressions assume linearity, we now present results for the relation between return predictors and bond returns using portfolio sorts. We sort bonds into deciles based on the characteristics and calculate both equal-weighted and value-weighted excess bond returns. Value-weighting is done using the prior month's market capitalization of the bond. We perform the sorting annually (at the end of January) and hold the portfolios over the next year for the variables PROF, ASTG, and RATG. We sort at the end of each month and hold the portfolios over the subsequent month for portfolios based on REQ26, REQ1, RBD26, RBD1, and LEAMI. Most of the equity market variables have greater standard deviations for junk bonds than they do for IG bonds. As a result, the extreme portfolios are likely to have more junk bonds than IG bonds when sorted into portfolios based on these equity characteristics. Thus, we check

TABLE 9

Monthly Cross-Sectional Regressions for Bond Returns: Time Variation in Coefficients

Table 9 presents the results when we first run the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma_{1t}' Z_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, and Z_{it-1} represents lagged return predictors, which are described in Table 2. We then run a time-series regression of the slope, γ, coefficients on lagged predictor variables as follows:

$$\gamma_{1t} = c_0 + c_1' X_{t-1} + u_t,$$

where the three X variables are the PAYOUT, the TRM_SPR, and the DEF_SPR. PAYOUT is the ratio of the sum of the last 12 months' dividends to the price of the Standard & Poor's 500 (S&P 500) index. TRM_SPR is the difference in the yield on long-term government bonds and the 3-month Treasury bill rate. DEF_SPR is the difference in the yields on BAA- and AAA-rated bonds. c_1 coefficients are reported for each γ_1 coefficient. t-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014.

Variable	PAYOUT	TRM_SPR	DEF_SPR
ln(MC)	2.03	0.11	11.36
	(1.10)	(0.08)	(1.63)
ln(BM)	2.07	0.76	3.56
	(1.43)	(0.99)	(1.15)
REQ26	−2.19**	−0.01	2.85
	(−2.47)	(−0.01)	(1.09)
REQ1	−3.77**	0.82	5.18
	(−2.72)	(0.68)	(1.12)
PROF	2.17*	−1.18*	1.59
	(1.85)	(−1.84)	(0.64)
NETISS	0.34	0.55	−0.53
	(0.29)	(0.85)	(−0.27)
ACCRU	−1.36	−0.25	−2.55
	(−1.23)	(−0.49)	(−1.35)
ASTG	0.60	−0.28	1.00
	(0.76)	(−0.54)	(0.59)
SUE	0.67	1.24	1.12
	(0.57)	(1.59)	(0.46)
IVOL	0.36	1.09	0.03
	(0.27)	(1.21)	(0.01)
RBD26	−1.81	0.84	−25.51**
	(−1.03)	(0.68)	(−3.73)
RBD1	6.16**	0.89	−18.63**
	(2.43)	(0.51)	(−2.41)
DD	2.38	0.53	0.57
	(1.40)	(0.41)	(0.20)
LEAMI	−0.95	−0.92	−0.42
	(−0.76)	(−1.17)	(−0.20)
ln(ISZ)	0.36	0.18	1.95
	(0.34)	(0.30)	(0.54)
ln(MAT)	2.20	3.84*	−0.32
	(1.10)	(1.68)	(−0.03)
LEV	2.55**	0.73	5.46**
	(2.12)	(0.79)	(2.41)
RATG	−0.18	−0.52	4.99
	(−0.09)	(−0.36)	(0.88)

the relation between equity return predictors and bond excess returns both for the entire sample and the subsamples of IG and junk bonds. Panel A of Table 10 presents the results for the long–short (H–L) portfolios that is long the 10th decile and short the 1st decile. For brevity, we focus only on the more robust equity and bond characteristics that impact the bond returns.

TABLE 10

Returns on Bond Portfolios from Characteristic Sorts

In Panel A of Table 10, we sort bonds into deciles and calculate both equal-weighted (EW) and value-weighted (VW) returns. The bond and equity characteristics are described in Table 2. Value weighting is done using the prior month's market capitalization. We sort at the end of January of every year and hold these portfolios for 1 year for the variables PROF and ASTG. We sort at the end of each month and hold these portfolios for 1 month for the variables REQ26, REQ1, RBD26, RBD1, LEAMI, and RATG. Sorts on RATG use only two portfolios: short on IG bonds and long on junk bonds. Excess bond return is calculated in excess of the matching Treasury bond that has the same coupon and repayment. We then calculate returns on a hedge portfolio (H–L) that is long in the 10th decile and short in the 1st decile. We form all of these portfolios for the sample of all bonds, as well as for the subsample of IG and junk bonds. We report only the hedge portfolio returns for the subsamples. In Panel B, we show the alphas from the time-series regressions of value-weighted bond returns, $R_{i,t}=\alpha_i+\beta_i' F_t+\epsilon_{i,t}$, where F_t are the factors used in the asset pricing model. The factors are the market factor, stock size and value factors, and firm investment profitability factors from Fama and French (2015); 2 bond factors (TRM and DEF); and the Pástor and Stambaugh (2003) liquidity factor. TRM is the return on long-term Treasury bonds in excess of T-bills, and DEF is the return on the corporate bond market portfolio in excess of the long-term Treasury bond. All returns and alphas are in percentage per month. t-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014.

Panel A. Bond Returns

	Equal-Weighted Returns			Value-Weighted Returns		
Variable	All	IG	Junk	All	IG	Junk
REQ26	0.13**	0.10**	0.42**	0.14**	0.10**	0.52**
	(2.08)	(2.91)	(4.15)	(2.47)	(2.64)	(4.84)
REQ1	0.49**	0.22**	0.75**	0.45**	0.23**	0.77**
	(8.15)	(6.27)	(7.59)	(8.82)	(5.93)	(8.59)
PROF	−0.19**	−0.05	−0.38**	−0.11**	−0.05	−0.22**
	(−4.44)	(−1.57)	(−3.03)	(−2.12)	(−1.55)	(−2.64)
ASTG	−0.14**	−0.08**	−0.19**	−0.11**	−0.07**	−0.04**
	(−4.82)	(−4.11)	(−2.99)	(−3.82)	(−2.81)	(−0.46)
RBD26	0.16*	−0.03	0.46*	0.03	−0.04	0.12
	(1.71)	(−0.42)	(1.89)	(0.36)	(−0.51)	(1.17)
RBD1	−1.12**	−1.32**	−0.88**	−1.30**	−1.34**	−1.21**
	(−9.34)	(−12.39)	(−3.70)	(−13.34)	(−12.76)	(−10.86)
LEAMI	0.32**	0.06*	0.27**	0.23**	0.06*	0.10
	(4.47)	(1.78)	(2.95)	(3.31)	(1.64)	(1.19)
RATG	0.31**	—	—	0.24**	—	—
	(5.78)			(4.97)		

Panel B. Bond Alphas

Variable	All	IG	Junk
REQ26	0.11*	0.10**	0.50**
	(1.87)	(2.97)	(4.43)
REQ1	0.43**	0.23**	0.75**
	(8.11)	(6.07)	(8.32)
PROF	−0.10**	−0.01	−0.13
	(−2.50)	(−0.23)	(−1.55)
ASTG	−0.07**	−0.07**	−0.12*
	(−2.27)	(−3.14)	(−1.84)
RBD26	−0.01	−0.05	0.10
	(−0.08)	(−0.55)	(0.82)
RBD1	−1.30**	−1.37**	−1.19**
	(−13.60)	(−13.13)	(−10.18)
LEAMI	0.17**	0.05	0.10
	(3.15)	(1.29)	(1.27)
RATG	0.16**	—	—
	(4.06)		

Consider the 1-month lagged equity return, REQ1, which has the highest and most significant coefficients among the equity characteristics. The monthly hedge portfolio returns range from 0.22% to 0.77% (2.6% to 9.2% annually). The effect is more pronounced for junk bonds, but IG bonds also show a significant lead–lag effect. In Section III.A.2, we propose the delayed reaction hypothesis and the overreaction hypothesis, which postulate opposite (respectively, positive and negative) signs on REQ1. The results in Table 10 support the former hypothesis.

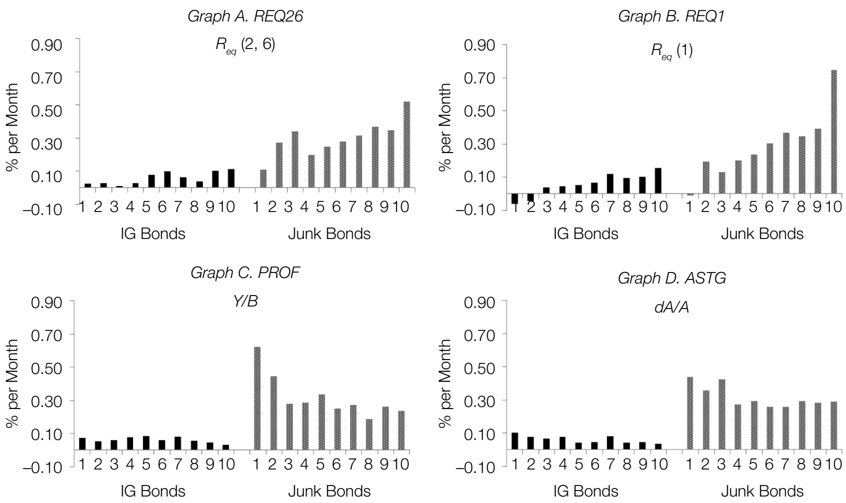
In Figure 1, we plot the average bond returns to the equal-weighted decile portfolios for the variables REQ26, REQ1, PROF, and ASTG, separately for IG and junk bonds. The predictive effect of the variables is clearly more pronounced in junk bonds.[17]

In general, the hedge portfolio results are consistent with the Fama–MacBeth (1973) regression results of Table 5. The only exception is bond momentum, RBD26. The univariate, equal-weighted hedge portfolio return when sorting on RBD26 is actually positive, especially for junk bonds. The hedge portfolio based on this characteristic yields an average return of more than 1% per month.

FIGURE 1

Hedge Portfolio Returns for Investment-Grade and Junk Bonds

Figure 1 shows returns for investment-grade (IG) and junk bonds. Return predictors are described in Table 5. We sort bonds into deciles and calculate equal-weighted excess bond returns. Excess bond return is calculated in excess of the matching Treasury bond that has the same coupon and repayment. We sort at the end of January of every year and hold these portfolios for 1 year for the variables PROF and ASTG. We sort at the end of each month and hold these portfolios for 1 month for the variables REQ26 and REQ1. Excess bond return is calculated in excess of the matching Treasury bond that has the same coupon and repayment. We form these portfolios for the subsample of IG and junk bonds and show the returns on these decile portfolios. All returns are in percentage per month. The sample period is 1973–2014.



[17]We replicate Figure 1 for the sample consisting of only the TRACE data (which are more comprehensive than the data in the other databases), which results in a significant loss of sample size. Nevertheless, the qualitative aspects of the figure remain unchanged.

We now check whether the excess returns can be explained by factor models. We calculate factor-model alphas from the following time-series regression:

$$R_{it} = \alpha_i + \sum_k \beta_{ik} f_{kt} + \varepsilon_{it}. \tag{6}$$

Our risk-adjustment framework is the 5-factor model of Fama and French (2015) (which includes the market factor plus those based on size, book-to-market ratio, profitability, and investment), augmented by the Pástor and Stambaugh (2003) liquidity factor, and 2 bond factors TRM and DEF (Fama and French (1993)).[18] Panel B of Table 10 presents the alphas from these time-series regressions for the value-weighted hedge portfolios. The results using equal-weighted portfolios are very similar to those reported here and are thus omitted. We find that the absolute alphas and their statistical significance are generally lower relative to those for raw returns. Also note that after adjustment for risk via the factor model both the magnitude and significance of profitability and asset growth decline. The fact that the significance of PROF declines in the factor model that includes profitability indicates that the profitability factor at least partially captures the increased risk of holding bonds of less profitable firms. Similarly, the risk adjustment including the investment factor at least partially captures the notion that firms with high asset growth have higher investment levels and thus lower discount rates.

Turning now to the bond market characteristics and equity liquidity, we find that with the exception of bond market momentum, the other predictors all remain significant with risk adjustment. Notably, whereas the coefficient magnitudes of RATG and liquidity decrease after controlling for the factors, the coefficient of the 1-month lagged bond return does not decrease following risk adjustment. Given that the impact of bond momentum is not robust to risk adjustment in univariate sorts, we now study it in more detail in the Fama–MacBeth (1973) regressions by considering the momentum effect in isolation and in the presence of other bond and equity characteristics. Table 11 confirms that although the univariate impact of bond momentum is positive, this impact turns significantly negative in the presence of other bond and equity characteristics. The coefficient on bond momentum changes from 7.78 in the univariate case to -15.71 in column 6, which includes all of the equity and bond market variables, and also becomes negative and highly significant in column 3, which includes only the bond market controls. Further investigation finds that this shift in the coefficient is due to the familiar sign flip that often occurs when regressors are highly correlated with each other (e.g., see Miller (2013)).[19]

[18] We also calculate alphas by including factors constructed from bond returns. For each of the characteristics, PROF and ASTG, we form 3 portfolios separately for IG and junk bonds and then take the average of the two hedge portfolio excess returns to construct the bond factor. We add these bond factors to the factor model and calculate alphas from the augmented model. In unreported results, we find that the new alphas are mostly similar to those reported in Table 10.

[19] Suppose that a variable Y is regressed on X_i $(i=1,2)$. Let the covariances between Y and X_i be $c_i > 0$, v_i be the variance of X_i, and $v_{12} > 0$, the covariance between X_1 and X_2. Note that in this case, the coefficients in univariate regressions when Y is regressed on X_i are both positive. However, the coefficient on X_i in the multiple regression is $(c_i v_j - c_j v_{12})/(v_1 v_2 - v_{12}^2)$ $(j \neq i)$. As can be seen from this expression, if the covariation between X_1 and X_2 is strong, that between Y and X_2 is low, whereas that between Y and X_1 is high, then X_1 (X_2) ends up with a positive (negative) coefficient

TABLE 11

Monthly Cross-Sectional Regressions for Bond Returns: Bond Momentum from RBD26

Table 11 presents the results from running the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma'_{1t} Z_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, and Z_{it-1} represents lagged return predictors, which are described in Table 2. We explore various combinations of right-hand-side variables together with RBD26. Regression 6 in Table 11 is identical to regression 9 in Table 5. *t*-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014.

Variable	1	2	3	4	5	6
ln(MC)				−5.19**	−6.77**	−1.17
				(−3.46)	(−3.97)	(−0.54)
ln(BM)				0.22	0.02	−3.04
				(0.22)	(0.02)	(−1.95)
REQ26				6.72**	9.54**	9.67**
				(7.20)	(9.22)	(8.72)
REQ1				9.40**	12.83**	12.68**
				(6.72)	(8.63)	(7.21)
PROF				−4.16**	−4.92**	−5.06**
				(−3.72)	(−3.89)	(−3.73)
NETISS				0.94	1.50	−0.27
				(0.67)	(0.79)	(−0.21)
ACCRU				0.70	1.37	1.34
				(0.75)	(1.13)	(1.14)
ASTG				−1.74	−2.79**	−2.00**
				(−1.49)	(−2.61)	(−2.22)
SUE				−0.86	−0.37	−0.25
				(−0.63)	(−0.25)	(−0.18)
IVOL				1.86	1.70	−0.75
				(1.43)	(1.10)	(−0.46)
RBD26	7.78*	1.51	−11.78**	−3.06	−12.75**	−15.71**
	(1.71)	(0.32)	(−5.14)	(−1.27)	(−4.95)	(−6.42)
RBD1		−30.49**	−41.72**		−44.59**	−47.54**
		(−8.16)	(−12.42)		(−12.21)	(−13.06)
DD			0.37			−2.39
			(0.25)			(−1.30)
LEAMI			2.91**			2.95**
			(2.82)			(2.01)
ln(ISZ)			−0.77			−1.29
			(−0.74)			(−1.01)
ln(MAT)			−5.52			−4.74
			(−1.57)			(−1.31)
LEV			0.76			−0.96
			(0.81)			(−0.72)
RATG			8.70**			7.13**
			(4.21)			(2.86)

The highest hedge portfolio returns occur due to the 1-month bond reversal. However, the 1-month reversal is often viewed as a compensation for liquidity (Grossman and Miller (1988), Avramov, Chordia, and Goyal (2006),

in the multiple regression. The statistical intuition is that X_2 'pulls down' the univariate effect of X_1 by accounting for the fact that X_1 only noisily explains Y. In our case, the key variable that causes RBD26's sign flip across columns 1 and 3 is RATG, whereas across columns 1 and 6, it is REQ26. Both of these variables are positively correlated with RBD26 and with the dependent variable, but RBD26's correlation with the dependent variable is much smaller than the corresponding correlations of RATG and REQ26 with that variable. These magnitudes account for the sign flip of RBD26.

Conrad et al. (1997), and Cheng, Hameed, Subrahmanyam, and Titman (2017)). We now test whether bond reversal is driven by illiquidity. We use the noise measure of Hu et al. (2013) to proxy for overall bond illiquidity. In Table 12, we regress the hedge portfolio returns (formed by sorting on RBD1) on the noise measure. The results show that the coefficient on NOISE is negative and significant, confirming that during periods of high illiquidity, corporate bonds experience higher reversals. This accords with the view that the reversal effect is compensation for illiquidity.

The next section investigates whether profits from anomaly-based bond market strategies survive transaction cost considerations and also considers the reward-to-risk ratios of these strategies.

TABLE 12

Bond Reversal Portfolio Returns

In Table 12, we form equal- and value-weighted decile portfolios as described in Table 10 for sorts on RBD1, the lagged monthly return on bonds. We calculate returns on a hedge portfolio (H–L) that is long in the 10th decile and short in the 1st decile. We form all of these portfolios for the sample of all bonds. We run the following regression of bond portfolio returns on the lagged noise measure, NOISE, of Hu et al. (2013):

$$R_{pt} = \gamma_0 + \gamma_1 \text{NOISE}_{t-1} + \epsilon_{pt}.$$

All returns are in percentage per month. t-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is Jan. 1987–Dec. 2014.

Variable	Equal-Weighted Returns	Value-Weighted Returns
γ_1	−0.09**	−0.09**
	(−2.26)	(−2.23)
$\overline{R}^2$	0.01	0.01

IV. Transaction Costs and Bond Return Predictability

A. Hedge Portfolio Returns Net of Trading Costs

An important issue is the economic and statistical significance of the returns from predictor-based bond portfolios after accounting for trading costs. We estimate portfolio transaction costs using two approaches. We first use the Bao et al. (2011) measure (BPW) of bid–ask spreads. Bao et al. show that the Roll measure provides more conservative estimates of effective transaction costs than quoted bid–ask spreads. We compute transaction costs as the product of the portfolio turnover and the time-series mean of the cross-sectional average effective spread. We report portfolio turnover, trading costs, and returns net of transaction costs for the hedge portfolios in Panel A of Table 13. For ease of interpretation, we normalize all hedge portfolio gross returns to be positive; that is, for example, the REQ1-based strategy is long high-REQ1 firms and short low-REQ1 firms, the PROF-based strategy shorts the most profitable firms and goes long on the least profitable firms, and so on.

Panel A of Table 13 shows that, unsurprisingly, portfolio turnover is relatively low (high) for portfolios sorted annually (monthly). This leads to lower

TABLE 13

Transaction Costs for Bond Portfolios

In Table 13, we form value-weighted decile portfolios as described in Table 10. Return predictors are described in Table 2. We calculate returns on a hedge portfolio (H–L) that is long in the 10th decile and short in the 1st decile. We form all these portfolios for the sample of all bonds, as well as for the subsample of IG and junk bonds. For ease of interpretation, we normalize all hedge portfolio gross returns to be positive. We then calculate trading costs following Bao et al. (2011) in Panel A and following Edwards et al. (2007) in Panel B. Portfolio transaction costs are calculated as the product of the portfolio turnover and the trading costs. Returns are reported net of these transaction costs. All returns are in percentage per month. *t*-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014.

		Trading Costs			Net Returns		
Variable	Turnover	All	IG	Junk	All	IG	Junk
Panel A. Trading Costs from Bao et al.							
REQ26	0.87	1.32	1.04	1.60	−1.01 (−17.82)	−0.84 (−22.89)	−0.91 (−8.50)
REQ1	1.76	1.31	1.02	1.62	−1.84 (−35.83)	−1.56 (−40.36)	−2.04 (−22.90)
PROF	0.08	1.25	1.00	1.43	0.01 (0.23)	−0.02 (−0.72)	0.08 (0.99)
ASTG	0.12	1.09	0.94	1.28	−0.02 (−0.58)	−0.04 (−1.69)	−0.13 (−1.67)
RBD26	1.04	1.60	1.32	2.06	−1.64 (−20.01)	−1.47 (−17.88)	−1.81 (−17.73)
RBD1	1.77	1.59	1.35	2.01	−1.52 (−15.68)	−1.10 (−10.47)	−2.32 (−20.72)
LEAMI	0.36	1.21	1.17	1.41	−0.21 (−3.13)	−0.45 (−12.53)	−0.51 (−6.06)
RATG	0.01	1.17	—	—	0.23** (4.77)	—	—
Panel B. Trading Costs from Edwards et al.							
REQ26	0.87	0.18	0.16	0.30	−0.02 (−0.29)	−0.05 (−1.30)	0.25 (2.34)
REQ1	1.76	0.18	0.16	0.30	0.14** (2.68)	−0.05 (−1.34)	0.25 (2.75)
PROF	0.08	0.18	0.16	0.30	0.09* (1.85)	0.04 (1.19)	0.19 (2.29)
ASTG	0.12	0.18	0.16	0.30	0.09** (3.10)	0.05** (2.04)	0.00 (−0.04)
RBD26	1.04	0.18	0.16	0.30	−0.16 (−1.93)	−0.14 (−1.72)	−0.16 (−1.58)
RBD1	1.77	0.18	0.16	0.30	0.98** (10.07)	1.05** (10.01)	0.69** (6.14)
LEAMI	0.36	0.18	0.16	0.30	0.16** (2.36)	−0.01 (−0.30)	−0.03 (−0.35)
RATG	0.01	0.18	—	—	0.24** (4.94)	—	—

transaction costs for annually sorted portfolios relative to the monthly counterparts. For the full sample, we find that net returns are negative for all the characteristic-sorted hedge portfolios except for that formed by sorting on RATG. Net returns are strongly and statistically significantly negative for lagged stock and bond returns as well as the Amihud illiquidity measure. Thus, despite its strong significance, the lead–lag effect does not provide profitable trading opportunities for investors net of transaction costs. Net returns from portfolios formed on profitability and asset growth are indistinguishable from 0. With regard to the bond market predictors, aside from DD, none of the other predictors yield a profit net of transaction costs.

We also use the trading cost estimates based on Edwards et al. (2007), who use an econometric model to estimate effective trading costs. They report these costs for different trade sizes and for different bond characteristics, such as the credit rating of the bond. In our analysis, we use Edwards et al. estimates for an institutional order size of $1 billion (Edwards et al. report a median institutional order size of $1.15 billion). The relevant numbers from Edwards et al. for our sample are trading costs of 18 bps, 16 bps, and 30 bps for all bonds, IG bonds, and junk bonds, respectively. We repeat the earlier analysis of calculating transaction costs as the product of portfolio turnover and these Edwards et al. trading-cost estimates. The results are reported in Panel B of Table 13.

Because the Edwards et al. (2007) trading costs are far lower than those of Bao et al. (2011), the net returns are higher in Panel B of Table 13 than those in Panel A. Net returns are positive for portfolios sorted on REQ1 and PROF for all bonds and junk bonds; they are positive for ASTG-sorted portfolios for all bonds and IG bonds; in the case of sorting on REQ26, the net returns are positive for junk bonds; when sorting on the Amihud illiquidity measure, the net returns are positive for all bonds; and finally, the net returns are positive when sorting on RATG. However, Bao et al. (p. 913) argue that the Edwards et al. measure is biased downward because it "does not fully capture many important aspects of liquidity such as market depth and resilience." Based on this argument, and thus accepting the Bao et al. measure as a reasonable estimate of trading costs, the only predictor that robustly survives transactions costs is RATG. This variable can be motivated by the RR paradigm, in that it is linked to the likelihood of distress (Fama and French (1993), Merton (1974)). Because risk-based predictors do not present a true arbitrage opportunity, our overall findings are consistent with the notion that bonds are priced up to transactions costs in a manner that does not imply arbitrage opportunities.

B. Sharpe Ratios of Hedge Portfolios

There remains the issue of whether the magnitude of the predictability documented in Section III.C.4 is consistent with risk pricing or a behavioral model. This translates to the following question: Are the rewards per unit risk from predictor-based strategies within bounds consistent with a rational, risk-based setting, or unduly high? To address this issue, we follow MacKinlay (1995) in calculating the Sharpe ratios of the characteristics-based hedge portfolios, both gross and net of trading costs, and compare these to a threshold below which the ratios accord with risk-based pricing.

The exact method is as follows. For each characteristic, we form value-weighted decile portfolios as described earlier. We then calculate alphas for each decile using the factor model used in Panel B of Table 10. The Sharpe ratio for raw returns is defined simply as the ratio of average portfolio returns to the standard deviation of the returns. We also calculate a ratio of alpha to the standard deviation of the residuals from the time-series regression that determines the alpha. This latter ratio can be interpreted as the Sharpe ratio of the optimal orthogonal portfolio, which is a portfolio of the original test assets that can be combined with the factor portfolios to form the tangency portfolio (see MacKinlay (1995) for further details). MacKinlay recommends a comparison of the resulting Sharpe ratio to 0.173, which corresponds to an annualized Sharpe ratio of 0.6, to determine if the ratio exceeds a reasonable magnitude for a risk-based predictor. Henceforth, we term this bound M. We calculate the p-value of the upper tail probability associated with this null of M. The standard errors of the Sharpe ratios (used for p-values) are computed by applying the delta method and using standard errors corrected with the Newey–West (1987) method. For ease of interpretation, we again normalize all hedge portfolio returns and alphas to be positive.

Table 14 provides the Sharpe ratios and the associated p-values. We only present results for the full sample; the results are similar for the IG and junk bond subsamples. It can be seen that of the 4 equity-based and 4 bond-based characteristics under consideration, only 2 characteristics, REQ1 and RBD1, have Sharpe ratios robustly higher than M. We repeat the analysis for net returns using

TABLE 14

Sharpe Ratios of Hedge Portfolios

In Table 14, we form value-weighted decile portfolios as described in Table 10 and calculate raw returns and alphas for these portfolios. Return predictors are described in Table 5. For the alphas, the factors used are the market factor, stock size and value factors, and firm investment and profitability factors (from Fama and French (2015)); 2 bond factors (TRM and DEF); and the Pástor and Stambaugh (2003) liquidity factor. TRM is the return on long-term Treasury bonds in excess of T-bills, and DEF is the return on the corporate bond market portfolio in excess of the long-term Treasury bond. The monthly Sharpe ratios of the extreme hedge (H–L) portfolios are reported for each sort. The return-based Sharpe ratio is the ratio of average returns to the standard deviation of the returns, and the Sharpe ratio for alphas is the ratio of alpha to the standard deviation of residuals from the time-series regression that estimates the alpha. The standard errors of the Sharpe ratios are calculated by applying the delta method and Newey–West (1987) correction using 5 lags. The null hypothesis is that the monthly Sharpe ratio is 0.173, corresponding to an annualized Sharpe ratio of 0.6. The p-value is the upper-tail probability associated with this null and is reported in parentheses below the Sharpe ratio. Columns 1 and 2 present the results using gross returns. Columns 3 and 4 present the results using net returns after adjusting for the trading costs from Bao et al. (2011). Columns 5 and 6 present the results using net returns after adjusting for the trading costs from Edwards et al. (2007). SR(R) represents the Sharpe ratio based on raw returns, whereas SR(α) represents the alpha-based Sharpe ratio. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014.

	Gross Returns/ Alphas		Net of Bao et al.		Net of Edwards et al.	
	SR(R)	SR(α)	SR(R)	SR(α)	SR(R)	SR(α)
Variable	1	2	3	4	5	6
REQ26	0.12	0.10	−0.85	−0.92	−0.01	−0.04
	(0.88)	(0.93)	(1.00)	(1.00)	(1.00)	(1.00)
REQ1	0.46**	0.45**	−1.86	−1.95	0.14	0.12
	(0.00)	(0.00)	(1.00)	(1.00)	(0.78)	(0.79)
PROF	0.10	0.12	0.01	0.01	0.09	0.11
	(0.92)	(0.85)	(1.00)	(1.00)	(0.95)	(0.91)
ASTG	0.14	0.10	−0.02	−0.08	0.11	0.07
	(0.79)	(0.95)	(1.00)	(1.00)	(0.92)	(0.99)
RBD26	0.02	0.00	−0.95	−0.98	−0.09	−0.11
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
RBD1	0.72**	0.74**	−0.85	−0.86	0.54	0.56
	(0.00)	(0.00)	(1.00)	(1.00)	(0.00)	(0.02)
LEAMI	0.16	0.16	−0.15	−0.24	0.11	0.10
	(0.63)	(0.64)	(1.00)	(1.00)	(0.89)	(0.93)
RATG	0.20	0.19	0.19	0.18	0.20	0.19
	(0.25)	(0.37)	(0.31)	(0.47)	(0.26)	(0.39)

Bao et al. (2011) and Edwards et al. (2007) in the last 4 columns. We find that none of the net Sharpe ratios is significantly larger than M, except RBD1 under the Edwards et al. measure; however, this characteristic does not yield high Sharpe ratios under the Bao et al. measure. Thus, the totality of the evidence suggests that, after adjusting for transaction costs, the predictability of bond returns using equity characteristics can be reconciled with risk pricing in corporate bond markets.

V. Conclusion

Corporate capital is raised from equity as well as debt markets. Although corporate bonds should be less sensitive to firm outcomes than equities, the volatility of corporate bonds is nontrivial and ranges between one-fifth and one-third of that in stocks (Acharya et al. (2013), Campbell et al. (2001)). Because uncertainty due to credit risk may share commonalities with stock payoff uncertainty, and investor biases could exhibit commonalities across stock and bond markets, it is important to ask whether bond markets exhibit cross-sectional return predictability similar to that in stocks.

Our analysis indicates that profitability, asset growth, and equity returns do predict bond returns, but other predictors, such as accruals, earnings surprises, and idiosyncratic volatility, do not. Although the asset growth effect in bonds is isomorphic to that in stocks, profitability negatively predicts bond returns, contrary to the sign of this variable for equities.

This evidence accords with the notions that firms with greater levels of real investment (and thus higher asset growth) have lower required returns, and small firms and those with low or negative profits are considered more risky by bond market investors, so their bonds command higher required returns. Consistent with these arguments, the economic and statistical significance of bond return predictors is attenuated once we control for risk using the Fama–French (2015) factor model which includes factors based on firm investment and profitability.

We also find that there is a significant lead from stocks to bonds at the monthly horizon, which indicates that new information is reflected in stock markets first. We compare anomaly-based Sharpe ratios to the bound suggested by MacKinlay (1995), below which a ratio accords with missing risk factors. Although several predictors are significant gross of transaction costs, the Sharpe ratios net of transaction costs do not robustly exceed the MacKinlay threshold for any of the predictors. Thus, overall, the evidence indicates that bonds are efficiently priced up to transaction cost bounds.

Our work suggests many extensions. The results suggest that the degree to which prices adhere to the RR paradigm depends on the clientele holding a security. This notion can be extended to other securities, such as warrants and preferred stock. In addition, the cross-sectional pricing efficiency of corporate bond markets in other countries remains an open question. These and other related issues are left for future research.

Appendix. Further Robustness Checks

Table A1 shows the descriptive statistics of the data across various databases.

TABLE A1

Summary Statistics on Bond Returns by Data Source

Table A1 presents summary statistics for all bonds used in the paper. Bonds are also divided into investment-grade (IG) and speculative grade (Junk) categories. Excess return is calculated in excess of the matching Treasury bond that has the same coupons and repayment schedule. AR1 is the first autocorrelation coefficient, and AR1–AR6 is the sum of the first 6 autocorrelation coefficients. No Price Change is the number of observations with no price change from the previous month. % Market Value is the time-series average of the ratio of the market value of bonds in a specific rating category to the total market value of all bonds. Mat is the average time to maturity in years. The sample period is 1973–2014.

					Excess Returns				
Category	*N*	No Price Change	% Market Value	Mat	Mean	Std. Dev.	Median	AR1	AR1–AR6
All									
All	924,859	16,912	100.0	12.2	0.11	2.93	0.10	−0.13	−0.11
IG	726,163	8,042	76.7	13.3	0.06	2.38	0.06	−0.24	−0.23
Junk	190,631	8,485	22.2	8.7	0.26	4.24	0.28	−0.01	0.02
Lehman Brothers									
All	643,016	13,155	25.2	13.9	0.07	2.92	0.07	−0.16	−0.18
IG	527,706	7,541	20.4	14.4	0.03	2.36	0.04	−0.28	−0.29
Junk	108,560	5,297	4.7	11.1	0.22	4.75	0.19	−0.02	−0.06
TRACE									
All	204,596	1,625	53.3	9.2	0.18	2.67	0.13	−0.08	0.04
IG	152,259	230	43.7	10.0	0.14	2.39	0.09	−0.13	−0.05
Junk	51,841	1,383	9.6	6.8	0.27	3.36	0.37	0.02	0.17
Mergent									
All	12,281	163	6.7	10.3	0.12	3.67	0.18	−0.16	−0.27
IG	7,363	40	5.6	12.2	−0.01	3.04	0.09	−0.22	−0.40
Junk	4,874	114	1.1	7.6	0.29	4.42	0.38	−0.11	−0.20
Datastream									
All	64,966	1,969	14.7	8.4	0.26	3.62	0.22	−0.03	0.10
IG	38,835	231	7.0	11.6	0.14	2.46	0.13	−0.16	−0.08
Junk	25,356	1,691	6.8	5.9	0.41	3.42	0.42	0.05	0.19

We run a series of tests to examine the robustness of the results in Table 5 to different data sources and the callability feature embedded in some bonds. The results are reported in Table A2.

Sample Excluding Matrix Prices. We exclude matrix prices from the Lehman Brothers Fixed Income Database. The results in Panel A of Table A2 are similar to those from the full sample. Surprisingly, the coefficient for REQ1 without matrix prices increases to 11.05 from 8.35 with matrix prices in full-sample regressions. Even without matrix prices, this lead–lag effect is the most significant forecaster of bond returns amongst the equity predictors, and the bond characteristics remain significant. This suggests that matrix prices are not stale in their response to lagged equity returns. There are no other statistically significant differences between the main results and the results from the subsample without matrix prices.

Sample Excluding Datastream. We exclude Datastream data from the sample. The inferences on predictors remain largely the same as those in the main sample; differences between the coefficients from the full sample and the subsample are statistically insignificant for all variables except PROF, whose effect is exacerbated.

Sample with Reverse Priority. For our main results, we prioritize the five data sets in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent

TABLE A2

Monthly Cross-Sectional Regressions of Bond Returns: Robustness Checks

Table A2 presents the results from running the following cross-sectional regression each month:

$$R_{it} \quad = \quad \gamma_{0t} + \gamma_{1t}' Z_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, and Z_{it-1} represents lagged return predictors, which are described in Table 2. Panel A presents the results when we do not include matrix prices in the bond sample. Panel B presents the results when we do not include Datastream in the bond sample. Panel C presents the results when we prioritize the databases in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent Fixed Income Securities Database/National Association of Insurance Commissioners (FISD/NAIC), and Datastream. Panel D presents the results when we include fixed effects for callable bonds in the cross-sectional regressions. In each panel, the columns entitled "Diff." show the difference of these results from those presented in Table 5. t-statistics with Newey–West (1987) correction (using 5 lags) are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is 1973–2014.

	Without Matrix Prices		Without Datastream		With Reverse Ordering of Databases		With Fixed Effects for Callable Bonds	
Variable	New	Diff.	New	Diff.	New	Diff.	New	Diff.
ln(MC)	0.92	−2.08	6.21	−7.38	−0.54	−0.62	−1.33	0.17
	(0.37)	(−1.33)	(0.86)	(−1.07)	(−0.26)	(−0.37)	(−0.59)	(0.49)
ln(BM)	−1.16	−1.88	28.77	−31.81	0.58	−3.62	−3.08**	0.04
	(−0.60)	(−1.44)	(1.00)	(−1.10)	(0.22)	(−1.28)	(−1.97)	(0.14)
REQ26	11.02**	−1.35	8.65**	1.02	12.01**	−2.34	9.65**	0.03
	(6.46)	(−0.96)	(6.85)	(1.14)	(4.14)	(−0.84)	(8.69)	(0.19)
REQ1	13.57**	−0.89	16.23**	−3.55	13.46**	−0.78	12.69**	−0.01
	(7.33)	(−1.49)	(2.58)	(−0.61)	(7.25)	(−0.70)	(6.94)	(−0.04)
PROF	−2.29	−2.77	0.29	−5.35	1.57	−6.63	−5.29**	0.23
	(−1.14)	(−1.26)	(0.06)	(−1.19)	(0.35)	(−1.30)	(−3.83)	(0.79)
NETISS	−0.80	0.53	−1.93	1.66	−1.86	1.59	−0.45	0.18
	(−0.54)	(0.95)	(−0.44)	(0.39)	(−0.88)	(1.00)	(−0.32)	(0.64)
ACCRU	−0.51	1.86	4.45	−3.11	−2.07	3.42	1.59	−0.25
	(−0.31)	(1.10)	(1.11)	(−0.76)	(−0.91)	(1.16)	(1.24)	(−0.89)
ASTG	−0.93	−1.07	−0.48	−1.52	0.26	−2.27	−2.02**	0.01
	(−0.66)	(−0.85)	(−0.19)	(−0.63)	(0.15)	(−1.28)	(−2.15)	(0.06)
SUE	0.62	−0.87	−6.33	6.08	−4.02	3.77	−0.01	−0.23
	(0.20)	(−0.28)	(−0.84)	(0.81)	(−1.02)	(0.97)	(−0.01)	(−0.70)
IVOL	2.20	−2.95	3.67	−4.42*	−1.07	0.33	−0.43	−0.32
	(0.70)	(−1.02)	(1.22)	(−1.70)	(−0.48)	(0.15)	(−0.24)	(−0.73)
RBD26	−19.22**	3.51**	−15.36**	−0.36	−15.74**	0.03	−15.79**	0.08
	(−7.19)	(3.33)	(−5.65)	(−0.19)	(−7.15)	(0.02)	(−6.60)	(0.39)
RBD1	−51.16**	3.62**	−46.43**	−1.10	−35.55**	−11.98**	−47.95**	0.41**
	(−13.85)	(2.70)	(−10.95)	(−0.51)	(−13.14)	(−3.97)	(−13.16)	(2.17)
DD	−0.71	−1.68	10.10	−12.49	−2.81	0.42	−2.30	−0.09
	(−0.28)	(−1.00)	(1.03)	(−1.24)	(−1.41)	(0.34)	(−1.23)	(−0.30)
LEAMI	3.28*	−0.33	10.90	−7.95	5.31**	−2.36	3.04*	−0.09
	(1.80)	(−0.23)	(1.53)	(−1.14)	(3.37)	(−1.43)	(1.86)	(−0.26)
ln(ISZ)	−2.68**	1.39*	0.58	−1.87**	0.04	−1.33	−1.70	0.41
	(−2.06)	(1.86)	(0.57)	(−2.93)	(0.04)	(−1.29)	(−1.33)	(0.99)
ln(MAT)	−3.31	−1.43**	−2.69	−2.04**	−5.26	0.52	−4.11	−0.63
	(−0.87)	(−1.97)	(−0.73)	(−2.57)	(−1.54)	(0.75)	(−1.13)	(−1.72)
LEV	0.35	−1.31	10.57	−11.53	−1.14	0.17	−1.13	0.16
	(0.21)	(−1.24)	(1.17)	(−1.25)	(−0.77)	(0.17)	(−0.88)	(0.73)
RATG	8.66**	−1.53	−0.33	7.46	6.61**	0.53	8.00**	−0.87
	(3.18)	(−0.90)	(−0.04)	(1.04)	(2.79)	(0.46)	(3.17)	(−1.76)

FISD/NAIC, Merrill Lynch, and Datastream. We now reverse this order. Panel C of Table A2 shows that the differences from the main results are small and statistically insignificant for all the anomalies we use.

Controlling for Callable Bonds. We repeat the cross-sectional regression with fixed effects for callable bonds. We do not report the coefficient on the fixed effects. Panel D of Table A2, however, shows that this has virtually no impact on the main results.

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